

SUSPENDED SEDIMENT YIELD MODELLING USING ARTIFICIAL NEURAL NETWORKS

Thesis

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By

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The tenure of human in this world is supported by many others. Acknowledgement for a few might be just a trifle thing written on a piece of paper. Nevertheless, in the true essence, it gives us an opportunity to remember and express our feelings to those, whom we love, revere and share our secrets. Here I get a great chance to complete this record.

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*June, 2016
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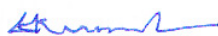
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CERTIFICATE

This is to certify that the thesis entitled **“SUSPENDED SEDIMENT YIELD MODELLING USING ARTIFICIAL NEURAL NETWORKS”** submitted in partial fulfilment of the requirements for the degree of **MASTER OF TECHNOLOGY** in **AGRICULTURAL ENGINEERING** with major in **SOIL AND WATER CONSERVATION ENGINEERING** of the College of Post Graduate Studies, G.B. Pant University of Agriculture & Technology, Pantnagar, is a record of bonafide research carried out by **Mr. DANIEL PRAKASH KUSHWAHA**, Id. No. **45499**, under my supervision and no part of the thesis has been submitted for any other degree or diploma.

The assistance and help received during the course of this investigation have been acknowledged.

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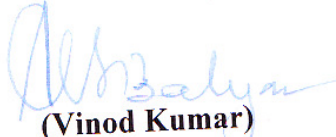

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Member

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LIST OF ABBREVIATIONS

ANFIS	Adaptive neuro fuzzy inference system
ANNs	Artificial neural networks
BP	Back propagation
CE	Coefficient of efficiency
CG	Conjugate gradient
<i>et al.</i>	And others
FFNN	Feedforward neural network
Fig.	Figure
FIS	Fuzzy inference system
GA	Genetic algorithm
GDX	Gradient descent
GEP	Gene Expression Programming
GP	Genetic Programming
g/l	gram/ litre
ha	hectare
i.e.	That is
J.	Journal
Km	Kilometre
L-M	Levenberg-Marquardt
LSTR	Longshore sediment transport rate
MAD	Mean absolute deviation
MAE	Mean absolute error
MAPE	Mean absolute percentage error
M ha	Million hectares
MLP	Multilayer Perceptron
MLR	Multiple liner regression
MSE	Mean square error
MUSLE	Modified universal soil loss equation
NMSE	Normalized mean square error

No.	Number
PARE	Pooled average relative error
Q_t	Discharge for current day
r	Coefficient of correlation
R^2	Coefficient of determination
RMSE	Root mean square error
RUSLE	Revised universal soil loss equation
Sci.	Science
sq. Km	Square Kilometre
SRC	Sediment rating curve
SSC	Suspended sediment concentration
S_t	Suspended sediment concentration for current day
SVM	Support vector machines
Tanh	Hyperbolic Tangent or tangent hyperbolic
VE	Volumetric error
viz.	Namely
$^{\circ}\text{E}$	Degree east
$^{\circ}\text{N}$	Degree north
%	Percent
Σ	Summation



Introduction



1. INTRODUCTION

Soil, one of the earth materials, is very important to sustain life on earth. Serious concerns in many parts of the world have been expressed for the accelerated erosion of soil caused by environmental disturbances, directly or indirectly, by human beings. Main contributing factors for occurrence of such problems are rapid urbanization, expansion of agriculture and deforestation which have changed the land use pattern. The geographical area of our country (India) is 328 M ha; out of which nearly 57% area is suffering from different types of erosion problems, mainly the soil erosion. Soil erosion by water leads to land degradation area, in India, it is nearly about 113.3 M ha. It has been estimated that about 5334 M tonnes of soil gets eroded annually (16.4 tonnes/year), and thus asking for the development, conservation and utilization of soil and water resources in such a way that high productivity and sustainability is ensured. These efforts of natural resource management will be meaningful only if attempted in a coordinated manner on a watershed basis.

Soil erosion not only reduces the quality of runoff water but also creates flooding of rivers. It deposits sediment at the bottom of reservoirs and rivers. Erosion of soil reduces the productivity of soil, leading to poor crop yield and silting of dams and reservoirs. Silting of dams and reservoirs causes less storage capacity of their structures. Directly or indirectly, such types of problems have caused intervention in morphology of rivers, reduction in carrying capacity of rivers, increase in sedimentation, process of eutrophication in reservoirs and frequent flood problems. Soil erosion due to runoff is considered to be the major cause for overall soil erosion and can be termed as one of the most land degradating phenomenon among natural calamities.

A significant role has been played by the research and other studies in the field of river engineering and dam engineering by predicting sediment load carried by river flow. Therefore, considerable emphasis has been given to resolve complex water resource management problems, where the key component for study was to develop deep understanding of sediment load estimation in rivers. Sediment may travel to the outlet of the catchment in the form of the suspended sediment or may roll over along the surface of the land as bed load. Various factors are responsible for causing

variability in sediment load. Among all factors rainfall as well as stream flow are the significant factors, which effect suspended load concentration (Jie and Yu, 2011). The quality of runoff and sediment yield also depends on the rainfall intensity, duration, initial soil moisture, land use and land cover, slope of the watershed etc.

In case of large watersheds, all the sub-watershed should be treated and developed on a priority basis to reduce soil loss and increase the land productivity. Conservation measures are of immense importance for all watersheds where such problems exist on a wide scale. Regional scale planning has been done on such typical watersheds to delineate hydrological models in order to achieve target rate values for soil conservation. Therefore, modelling of soil erosion rate has become necessary in such regions. On the basis of such governing processes, models can be categorised into two components viz. physics based models and system based theoretic models. In physics based models hydrologic behaviour of watershed is modelled through different physical processes. A number of physics based models or phenomenons, were proposed by researchers to evaluate and predict sediment yield. Till now, physics based models, empirical formulae, sediment rating curve (SRC), various statistical techniques, multiple linear regression, universal soil loss equation (USLE), MUSLE, RUSLE etc. have been used for prediction of sediment yield. Researchers have found it difficult to arrive at any fixed conclusion on a mechanism for sediment load transportation and non linear behaviour of selected hydrologic parameters which is difficult to model.

In system theoretic models, input data is transferred to the output zone with the help of transfer functions as they do not include any physical characteristics of input parameters. A great revolution has been observed in prediction and resolving hydrologic problems by various researchers when artificial neural networks were used as tool with any system theoretic model. The main character of a black box is to simulate complex natural processes, and therefore, it was considered of much significance when it was employed to solve different types of water resource problems.

Artificial neural networks, one of the most popular soft computing techniques, are examples of system theoretic models. They have been used to model water fluvial systems in the field of engineering and applied hydrology. Model development is

based upon input and output data, and no understanding of physical laws is required. Non linear systems, which can not be modelled by traditional methods, can be modelled by ANNs. ASCE (2000a, b) gave concepts of ANNs and its application in hydrology and its allied fields.

Details of watershed characteristics are not required in the application of ANNs and results obtained are closer to the observed ones, because ANNs uses both linear and non linear concepts for the development of model and can be performed with memory less or dynamic systems. Artificial neural networks have two main merits, the first one is to perform action without any dependence on the past events, and the second one is to overcome any inconsistency in data taken as the input or even if there is less availability of data.

In recent years, artificial neural networks based system theoretic models have been employed in solving hydrological and meteorological problems, such as, rainfall runoff modelling, runoff sediment modelling (Singh *et al.* 2013; Rai and Mathur, 2008; Kisi *et al.*, 2012; Gharde *et al.*, 2015; Jain, 2001;), river flow estimation (Nayak *et al.*, 2004), evapotranspiration process, optimization of water supply systems, ecological and hydrological response assessment on climate change, modelling of reservoir inflow and operation, remediation of ground water and prediction of ground water quality, drought forecasting etc.

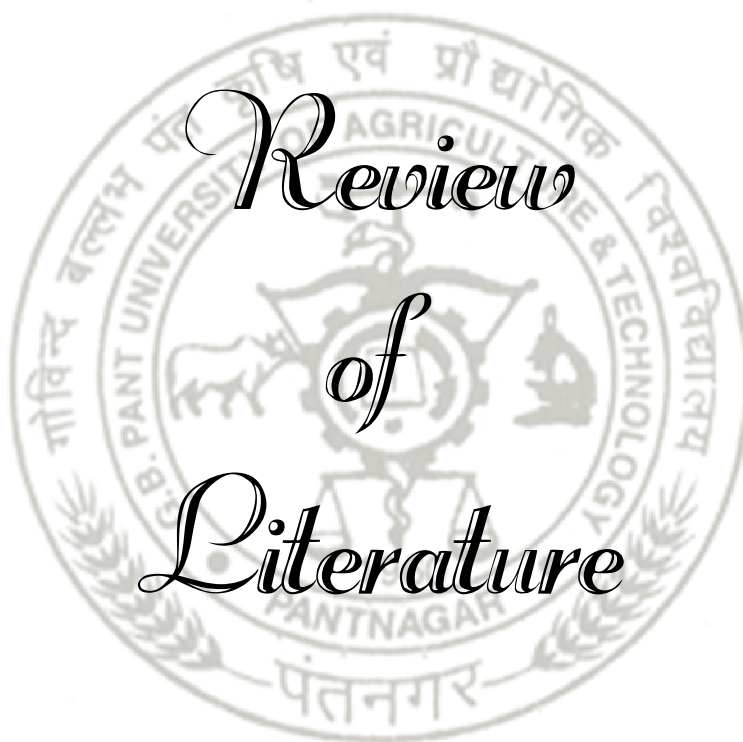
It was found that geomorphology based neural network is better than non geomorphology based neural network for sediment yield prediction (Sarangi and Bhattacharya, 2005). Imrie (2000) enhanced the generalization through a supervised system to the extrapolation properties and cascade correlation learning architecture by using a suitable activation function. Dawson and Wilby (1998) explained behaviour of an artificial neural network based rainfall runoff model. Danh (1999) and Elshorbagy (2000) predicted runoff by using two criteria i.e. fixed stopping criterion and independent variables, through feed forward error back propagation in ANNs and then the model was compared with the results obtained through available conceptual models.

The purpose of the present study is development, performance evaluation and application of artificial neural networks (ANNs) models for estimation of concentration of suspended sediment on a daily basis for the Baitarani river at

Anandpur station located at the outlet, and Champua station located at the top of the Baitarani river basin, falling in the state of Odisha, India.

To achieve this broad objective, present study is taken up with the following as the objectives of the study:

- i. To develop daily discharge- suspended sediment concentration models at Champua and Anandpur stations of Baitarani river basin by using artificial neural networks (ANNs) technique
- ii. To validate the developed models for the study river basin
- iii. To evaluate the performance of developed models and to identify the best suited models



*Review
of
Literature*



2. REVIEW OF LITERATURE

This chapter deals with the review of some of the studies conducted related to development and applications of artificial neural networks (ANNs) based models in hydrology.

ASCE (2000a) described an introduction of ANNs in hydrology. Apart from various descriptions of various aspects of ANN & some guidelines on their uses were presented. Overall analysis was done to count advantage and limitation of ANNs model when it was implemented to solve any complex hydrological problem. Results obtained were then evaluated with other modelling approaches i.e. physics based models.

ASCE (2000b) focused on that part of ANNs which was found to be useful for various branches of hydrology. The paper presents an excellent critical review of published work with identification of merits and demerits. Efficient neural network configuration and input vectors could be selected by developing deep understanding of hydrologic process through estimation of physics laws introduced in that process. ANN performance depends on type of data; therefore it can be used for any kind of data. Hence no fixed design was required for implementing ANNs in any hydrological problem.

Jain (2001) developed a relationship between sediment and discharge for two gauging stations of Mississippi river using ANNs models. The results obtained from ANNs technique were compared with existing methods. ANNs technique results were found to be nearer to the measured values.

Abrahart and White (2001) proposed the potential benefits for modelling sediment transfer. Some initial path finder experiments were conducted to assess the competence of a back propagation network to produce a combined model of sediment transfer which was traced during implementation of land management methods and when different type of agriculture practices were followed. The results of the investigation demonstrated that a neural network solution is able to exceed the limitations of traditional multiple linear regression.

Nagy *et al.* (2002) used ANNs in estimating suspended sediment concentration of rivers and to develop appropriate model to account it. Stream width

ratio with other variables like mobility number, Froude number, Reynolds number were taken as input parameters and all above gave output as results in the form of sediment concentration. Total 80 data observation were selected and used in different sediment discharge formulae and ANNs models. Results obtained were then compared which showed that ANNs results are really superior in comparison to any other method used for sediment discharge prediction.

Tayfur *et al.* (2003) implemented ANNs in bare soils for estimation of sediment load from these surfaces. For this purpose, a fuzzy logic algorithm was developed in which rainfall intensity and slope was taken as input variables. Fuzzy subsets were made from slope and rainfall intensity variables and then triangular membership function was assigned to them. Results obtained through this fuzzy algorithm were much similar to the observed data or to the sediment measured. Comparison between fuzzy models, ANNs models and physical based models indicate good performance of fuzzy models under this study when high values of rainfall intensities over different slope values with different values of rainfall intensities were feed as data input parameter.

Nayak *et al.* (2004) gave model for modelling hydrological time series and is explained by an application to model the river flow of Baitarani River in the state of Odisha, India through adaptive neuro-fuzzy inference system (ANFIS). Results obtained through adaptive neuro-fuzzy inference system based models were compared with artificial neural network results and also with other conventional models results to assess its accuracy and performance. Forecast error, computational speed, efficiency, estimation of peak flow etc. were adopted criteria for evaluation of performance among all these models.

Kisi (2004) predicted daily suspended sediment concentration for a particular cross-section of river, in which he compared then fuzzy logic model and the sediment rating curve model. Present study was performance at Quebrada Blanca, USA. Prediction for five year period when stream flow was assumed continuous was assessed for sediment concentration by comparing graphical and numerical values between fuzzy and sediment rating curve models. Total developed models used for study were nine for such stream flow. Superiority in prediction through fuzzy models was obtained than other methods like rating curve models when same data set was used to evaluate performance and accuracy.

Kisi (2005) compared two approaches, neuro-fuzzy model with neural network model approach during modeling of stream flow-sediment concentration relationship. Two stations Quebrada Blanca and another one was Rio Valeniano were taken for data input i.e. daily stream flow and suspended sediment data. MLP and SRC models were also developed for this research study. Results obtained through neuro-fuzzy model were much superior than other models during this study.

Cigizoglu *et al.* (2006) used ANN for suspended sediment estimation through implication of available data in model developed for this study. Optimum number of nodes selection for input dependent on statistical parameter analysis of stream flow and sediment data. Limited data availability could yield better results for sediment estimation when similarity between model calibration data statistics were much fine tuned with the model validation data as represented by the k-fold partition of the data set in training. Main character of range dependent neural network which was significant due to capability of training itself through single network by whole set of data used in calibration. RDNN estimated much closer values which were representation of its good command in prediction of values by correlating it with low and high observe values in data series.

Achite *et al.* (2007) used data of 22 hydrological years, started from 1873 to 1995 of wadi (Dry land River) in north western Algeria part of the country for estimation of fine sediment budget. Total data of about 702 entries were used to develop regression relationship between daily discharge daily suspended sediment concentration and daily sediment discharge. Main limitation of this regression techniques was found when it over estimate sediment values from 20% to 25% of the suspended sediment flux.

Bateni *et al.* (2007) estimated scour depth using sufficient length of data with the help of ANNs and ANFIS. Five variables used for modelling scour depth were; critical flow velocity, mean velocity, flow depth, pier diameter and mean grain diameter. Variation in scour depth time was measured through modelling by equilibrium scour time depth, scour time and critical and mean flow velocity. Prediction of scour depth by MLP back propagation model was observed better than radial basis function and ANFIS.

Dogan *et al.* (2007) used ANN to estimate daily suspended sediment load. This study was performed at Olter stream, Lyi stream, Harsitstream, Corath river in

Black sea region of turkey. ANFIS was used during this study for prediction of values with MLR and SRC. Statistical parameters of RMSE and R^2 showed that values obtained through ANFIS were of much accuracy than values predicted through MLR and SRC values.

Lohani *et al.* (2007) developed stage discharge relationship with sediment concentration to perform this study. Selected site for data collection was Narmada basin, India. Performance of this model was compared with that of sediment rating curve (SRC) and neural network (NN) models using various statistical indices like PARE, r, and RMSE. Fuzzy logic model gave much better results than SRC model which could be revealed by values obtained in these three combinations of soft computing techniques.

Azamathulla *et al.* (2008) focused on estimation of bed load data as the four bed load equation which was inn habit of using median sediment size (i.e. d_{50}) were unable to yield accurate results. In this study adaptive neuro-fuzzy inference system (ANFIs) was applied to predict bed-load data. Limitation of these four equations were found when they over predicted bed load dat and during testing trial not a single equation was able to perform satisfactory when all of them were employed in a local river. Data from Kinta River, pari, kerayong river and Langat river which amount to total data set of 346 bed load were used to develop the ANFIS. New set of data was then used to perform validation part of this trial. This new set of data was collected from kulim river. Overall results obtained indicate that ANFIS predict measured load much more efficiently.

Cohen *et al.* (2008) developed fuzzy based soil erosion model utilizing commonly used input data for watershed management purposes. After evaluating the model on small watershed, it was applied on watershed having medium size in Israel. For hydrological stations results of fuzzy based model were compared with measured runoff data. After that the model was applied in two watersheds. After comparison of fuzzy based models with other two models, it was concluded that fuzzy based model gave better results.

Kisi *et al.* (2008) developed a model using adaptive neuro-fuzzy technique for estimation of monthly suspended sediment from two stations in Turkey. Two different models were also developed by using sediment rating curves and artificial neural networks. The results of the neuro-fuzzy technique compared with those of the ANN

and SRC. Root mean squared errors, mean absolute errors and correlation coefficient were used as goodness of fit criteria for the evaluation of the models. The neuro-fuzzy method was found to be better than the other models. The comparison of the results revealed that the neuro-fuzzy models can be applied for monthly suspended sediment prediction in the watershed.

Khoob (2008) estimated reference evapotranspiration data from evaporation and maximum and minimum air temperature data using ANNs. The results were compared with FAO-56 Penman Monteith equation for SARC, Iran. The results shown that ANNs gave better estimates than FAO-56 Penman Monteith equations which under estimated the values of reference evapotranspiration.

Rai and Mathur (2008) applied a feedforward back propagation artificial neural networks based model for temporal variation of sediment yield estimation of events. The calibration of the model was done by using the gradient descent algorithm and with automated Bayesian regularization. Different ANNs structures were tried with different patterns of input. Finally, it was found that ANNs based model gives better result in comparison to the linear transfer function model for the estimation of runoff hydrographs and sedimentographs for both the study watersheds.

Nourani *et al.* (2009) investigated the artificial neural network wavelet model performance for simulation of rainfall-runoff hydrologic process in Lighvanchai basin, Iran. The wavelet analysis was applied to decompose the data series into approximation and detail series. These decomposed subseries were used as input into ANNs based model for prediction of river flow one day ahead. The results presented that the developed method could be used for prediction of both short term and long term river flows.

Cobaner *et al.* (2009) estimated sediment concentration from daily data of rainfall, discharge and suspended sediment by ANFIS. Various combinations of above parameters were used as input to model. The results of ANFIS were compared with three ANNs models and two rating curves. The results obtained from ANFIS were found to be better than the remaining models.

Picouet *et al.* (2009) modelled sediment concentrations during rising and receding of flood utilizing statistical approach. The second model was developed which was a lumped conceptual model using contributions from two sediment reservoirs. The first reservoir represented hill slope erosion and second reservoir

represented sediment deposit in channel and bank erosion. The results obtained from both the models were promising and simulated sediment concentration well for the annual values. However the results were poor in comparison to simple regression model.

Kabiri-Samani *et al.* (2010) estimated long shore sediment transport rate using technique of fuzzy logic and ANN. Variables considered in estimation of LSTR were wave breaking height, period, angle, grain size, beach slope and sediment mass flow rate. The result of fuzzy logic, ANNs, and empirical formulae were compared and it was observed that out of various approaches of ANNs and fuzzy logic, gradient descent approach is better and it was formed to be more accurate during this study.

Kisi (2010) developed neural differential evaluation models (NDEM) for sediment concentration estimations. The results of NDEM were compared with ANFIS, ANNs and rating curves. Sediment and discharge data of two stations were used in this study. The model's performance was evaluated using two statistical indices i.e. MSE and R^2 . The developed model gave better results in comparison to the other model used in this study.

Mirbagheri *et al.* (2010) used ANNs, WNF, NF and SRC models for sediment forecasting using discharge and sediment data taken from Rio Rosario station. The performance of NF model was found better than ANN and SRC models. The results indicated a very good agreement between the measured values and predicted values by NF models even for extreme values.

Rajaei (2010) applied NF, WNF, SRC and MLR models for suspended sediment modelling in USA. The values obtained from WNF model were found to be much more closer to the measured values and therefore gave better results in comparison to NF, SRC and MLR models. The cumulative suspended sediment load was also computed with reasonable degree of accuracy and even forecast for extreme values was good in case of WNF model.

Parthasarathi *et al.* (2010) combined Muskingum model and sediment rating model to develop an integrated water discharge sediment concentration model (WSCM) for a reach of Mississippi river. This single model is sufficient to explain the variation in sediment and discharge of the river. The performance of WSCM was compared with other existing model reported in the literature and it was observed that the performance of WSCM is good.

Yekta *et al.* (2010) used fuzzy logic and neural networks to predict the suspended sediment load as a function of discharge data and compared the results with rating curve method using measured data of Ekbatan reservoir sub basin located in the west of Iran, between 1964 and 2006. Results indicated that the developed intelligent methods, artificial neural networks and artificial neuro-fuzzy inference systems are more accurate than rating curve (RC). Study results also represent that the ANFIS is more accurate than ANNs for predicting of suspended sediment load as a function of discharge.

Kuo *et al.* (2011) demonstrated the efficiency of back propagation artificial neural networks (BPANNs) in forecasting reference evapotranspiration and pan evaporation in Chai Nan irrigated area of Taiwan. The reference evapotranspiration estimated by the pan evaporation was measured at that area and FAO-PM56 method. The results represented that the back propagation artificial neural networks (BPANNs) estimated the reference evapotranspiration better than pan evaporation.

Nayak and Jain (2011) Nayak predicted stage, discharge and sediment relationship through application of Sugero inference system of first order. Study was conducted on two rivers, one in USA and other one in India. Main aim was to estimate discharge and simulation of sediment concentration was also put as priority area for study. Fuzzy rules had been generated by help of clustering algorithm whose main component was least square estimation. Since, there lies a great variability in the discharge, stage, and sediment concentration relation, therefore fuzzy rules had been found to be of great importance. Fuzzy rules were trained by back propagation algorithm. Statistical indices like root mean square error and sum of square error mentioned superiority of neuro-fuzzy model over multi-linear and other conventional methods during prediction of such relationship.

Salajegheh *et al.* (2011) considered estimation and Modelling of sediment discharge nonlinearity using Artificial Intelligence i.e. multilayer perceptron, fuzzy logic and neuro-fuzzy techniques, for suspended load of Brandywine Creek watershed in Chester County, Pa at Chadds Ford station. Dataset were divided in three different parts of training, testing and validation. Four kind of different compounds of water and sediment dataset were used for learning process of model as inputs. The results show that these methods could model nonlinear relationship between water and sediment discharge accurately. The comparison of multilayer perceptron, fuzzy logic

and neuro-fuzzy methods and classic ones i.e. sediment rating curve and regression, show that multilayer perceptron had better application than classic ones and hybrid neuro-fuzzy modelling shows the best accuracy among all methods.

Kumar *et al.* (2011) developed the back propagation artificial neural network based models with Levenberg-Marquardt learning algorithm, radial basis function, fuzzy logic and decision tree algorithms such as M5 and REPTree for forecasting the suspended sediment concentration at Kasol, India. Statistical properties like partial auto correlation function, cross correlation function and auto correlation function of the time series were used for derivation of input vector to the models. It was observed that performance of M5 is better in comparison to other models.

Shabani *et al.* (2012) estimated daily suspended sediment in kharestan watershed in Iran with artificial neural networks model utilizing 25 years of sediment and runoff data. Results obtained by ANNs were compared with sediment rating curve making use of root mean square error, mean absolute error and coefficient of determination. The results obtained with ANNs were better and accurate than rating curve method.

Azamathulla *et al.* (2012) developed models for sediment load relationship using gene expression programming, adaptive neuro-fuzzy inference system and regression models for the three Malaysian rivers viz. Muda river, Langat river and Kurau river. On comparing the performance of these models on the basis of coefficient of determination, average and root mean square error, GEP model was found to be acceptable compared to ANFIS and better than the conventional models.

Chang *et al.* (2012) used gene expression programming, feed forward neural networks and adaptive neuro-fuzzy inference system soft computing techniques, to predict total bed material load for Malaysian rivers namely Kurau, Langat and Muda. The values of R^2 and RMSE for FFNN were found to be 0.958 and 0.0698, for ANFIS 0.648 and 6.654 and for GEP 0.97 and 0.057. Results show that these techniques can be used in the prediction of sediment loads for rivers of these regions.

Kisi *et al.* (2012) estimated daily suspended sediment by using flow and sediment data (from 1972 to 1989) of two stations of Cumberland river with the help of genetic programming. For modelling optimal operator, fitness and linking functions and learning algorithm were found. The results of genetic programming were compared with artificial neural networks, adaptive neuro-fuzzy inference system and

support vector machine. Based on statistical indices it was observed that genetic programming is better in comparison of other models used in this study for suspended sediment estimation.

Kisi and Shiri (2012) compared adaptive neuro-fuzzy inference system, artificial neural networks and gene expression programming for their accuracy in estimating of suspended sediment concentration, daily suspended sediment concentration, rainfall and stream flow data from Eel river were used in the study. It was found from the study that performance of gene expression programming model is better than the other models. Levenberg Marquardt learning algorithm, gradient descent and conjugate gradient training algorithms were used in ANNs models. Among the algorithms, the conjugate gradient algorithm was performing better than the others.

Muhammadi *et al.* (2012) performed this study at Karaj dam in which mainly two parameters i.e. discharge of water data base and temperature of water at entry site of dam was taken as input. ANN, ANFIS and SRC were used in modeling to resolve such problem of estimating sediment concentration. Results obtained were calculated in form of statistical parameters like root mean square error and correlation coefficient which finally represents that ANFIS performance was much better than SRC and ANN models.

Du *et al.* (2013) investigated the effects of rainfall and land use cover on runoff and sediment in Jinsha watershed. Runoff and sediment yield were found to be positively correlated with rainfall and negatively correlated with land use cover. Relative error of less than 5% in runoff forecasting by Adaptive neuro-fuzzy inference system shows its effectiveness. The method was found to be poor in sediment yield forecasting which clearly explain that rainfall and land use cover contribute only part of variation in sediment yield. Therefore other factors like human interference should be taken into consideration.

Eisazadeh *et al.* (2013) applied multiple linear regression (MLR) and neural network (NN) for estimation of sediment yield from 25 sub-basins of reservoir, by using 160 data sets of sediment yield. Study was conducted in west Azerbaijan province, Iran. Comparison of results of both MLR and NN models indicated that NN model predicted the sediment yield more accurately with R^2 and RMSE being 0.86

and 0.09 respectively than MLR models with R^2 and RMSE as 0.64 and 1.41 respectively.

Ghorbani *et al.* (2013) applied soft computing techniques at Rio Chama, a tributary of the Rio Grande river in the U.S. states of New Mexico and Colorado. SRC, MLR, ANNs, NF models were employed for estimation of suspended sediment load. Overall evaluation was done through statistical parameters selected during study like coefficient of determination, RMSE, coefficient of efficiency etc. Discharge in this study was used as input in ANNs while in fuzzy model main input parameters were sediment and discharge. Performance of these two models was much better than performance of other two models i.e. MLR and SRC. Results for annual sediment load was also predicted by NF and ANNs model to a much fixed tune, which shows their better prediction efficiency.

Wieprecht *et al.* (2013) applied ANFIs at river Rhine for prediction of bed load and total bed load. Parameter for developing model was mainly those which effect sediment transport on large scale. These four input parameters were 510, 560, total bed material load, measured bed load data. Nearly 70% of data was used for training and 30% for testing trial. To develop a perfect fuzzy model division of input parameters into grid form was done. ANFIS used in fuzzy model help in optimization of the model, which had capability to predict much similar results as was measured at the site. To maintain accuracy of the developed model, few important combination of input parameters, their numbers, type of membership functions were analyzed carefully. Overall performance of ANFIs as neuro-fuzzy model was so better in prediction of bed load and total bed- material load prediction.

Singh *et al.* (2013) focused on input parameter like monthly rainfall and runoff by two techniques of soft computation. Model was developed by using standard back propagation and radial basis model. Study was performed for a watershed in India. Type and number of inputs for development of model was done through four different scenarios. Point noted during study was addition of average discharge and monthly precipitation values to the neural network techniques which increased performance of the model to much higher level during estimation of monthly sediment yield. Optimization was done for both types of model developed by using two different techniques. Radial basis neural network gave much better results

of prediction than any other methods like standard back propagation for prediction of sediment yield at these watersheds.

Angabini *et al.* (2014) used fuzzy rule based model, artificial neural networks and fuzzy linear regression sediment rating curve methods for simulation and sediment concentration assessment of the Jagin dam. Runoff data, scale water stage and sediment density of Penhan station were used. Correlation coefficient and root mean square error were used as criteria of goodness of fit. Results indicated that fuzzy rule based model outperforms than other techniques.

Guner and Yumuk (2014) used combination of hybrid adaptive network fuzzy inference system for prediction of sediment transport. Models were developed using above technique which was a combination of neural network and fuzzy inference system input parameters was taken as breaking wave height, slope at the breaking point, breaking wave angle, peak wave period and medium grain size and one output i.e. longshore sediment transport rate. Scatter index, R^2 , correlation coefficient, RMSE were main statistical parameters used during study for evaluation of performance of these indices. Performance evaluation indicates that ANFIS model is better than other empirical and numerical models including FIS.

Heng and Suetsugi (2014) compared catchment similarity, spatial proximity and regression approaches for estimation of rating curves of sediment in 16 catchments, in the Lower Mekong Basin. The results obtained by catchment similarity approach were the best. The regression based approach was intermediate in terms of results obtained. The sparse network of watershed monitoring did not favor the spatial proximity approach. Accuracy of overall prediction was further improved when a combined formulation of catchment similarity and regression was made. It was observed that one of them can not be used for heterogeneous watersheds.

Nourani (2014) addressed the applications of artificial neural networks, genetic programming and support vector machine, adaptive neuro-fuzzy inference system, wavelet artificial neural networks and wavelet neuro-fuzzy models for forecasting and prediction of river and watershed sediment loads. Review suggests that artificial neural network for modelling suspended sediment load leads to acceptable results but in past few years more attentions are paid to apply hybrid models. Genetic programming also produces applicable results, but most of studies show that ANNs is more powerful tool than genetic programming. Employing Support Vector Machine shows accurate results

than other approaches; especially, when using selected kernels. No coincidence, application of hybrid models leads to better results in comparison with sole artificial intelligence based models. Preprocessing of data and handling non stationary data are the main reasons of such results.

Kumar *et al.* (2015) employed modified universal soil loss equation (MUSLE) and fuzzy logic based model for prediction of runoff and sediment yield for a reservoir basin of Megadrigedda reservoir situated at Visakhapatnam district in Andhra Pradesh, India. It was found out that both the fuzzy logic model and MUSLE show satisfactory results in simulation of the sediment yield.

Olyaie *et al.* (2015) compared the results obtained by using artificial neural networks, adaptive neuro-fuzzy inference system, coupled wavelet and neural network and conventional sediment rating curve approaches for estimating the daily suspended sediment load in two gauging stations in the USA. The values of correlation coefficient, coefficient of efficiency, root mean square error and mean absolute percentage error showed that all the models except sediment rating curve were in good agreement with the observed suspended sediment load values. The coupled wavelet and neural network was the most accurate model in suspended sediment load estimation in comparison to other models.

Rezaei and Fereydooni (2015) predicted suspended sediment load values by taking input parameter of rate of flow of sediment and monthly flow rate. Total data contain entries of 21 years i.e. 252 entries. Out of this data, calibration was performed by 80% of the data and validation was performed by 20% of the data. Statistical indices used for evaluation of these models were coefficient of correlation and root mean square error. Simulation of monthly suspended sediment load was done by implementing various techniques like Matlab software, ANN with sigmoid and tangent function which was used in hidden layer and also linear function which was used in output layer. In Dalaki Cham, chit, simulated value of sediment was predicted by applying values obtained through hydrometer. Results obtained were then evaluated against results of neuro-fuzzy inference system. ANFIs results were far better than results of artificial neural network.

Gharde *et al.* (2015) developed artificial neural network model for forecasting the sediment yield of Kal river in Maharashtra using the stream flow, stream flow lag

by one or two day, rainfall and sediment yield lag one or two day as input to the model. Multilayer feedforward back propagation neural network with one to three input layers, one hidden layers and one output layer were developed. The model performance was evaluated by statistical indices such as Nash-sutcliffe efficiency, correlation coefficient, volumetric error, mean absolute deviation, root mean square error and mean average percentage error were used for performance evaluation. The performance of model was better when input parameter and changing combination of inputs parameters increases. The performance of ANNs model was found better and overall performance were satisfactory for prediction of sediment yield.

Kermani *et al.* (2016) evaluated the ability of artificial neural networks and support vector regression models to forecast/estimate daily suspended sediment concentrations using eight years data from a station in USA. Three different ANN model algorithms (gradient descent, conjugate gradient and Broyden–Fletcher–Goldfarb–Shanno) were tested along with four different support vector regression model kernels (linear, polynomial, sigmoid and radial Basis function). The performance of the models was evaluated based on root mean square error, Pearson's correlation coefficient and Nash–Sutcliffe model efficiency. The ANNs and support vector regression models showed improvements in results over multiple linear regression and sediment rating curve models.

Bonakdari and Zaji (2016) introduced a new self neuron number adjustable, hybrid genetic algorithm-artificial neural networks and its application examined on the complex velocity field prediction of an open channel junction. The results of genetic algorithm-artificial neural network were compared with genetic programming method as two applications of the genetic algorithm. The comparisons showed that the genetic algorithm-artificial neural networks model can forecast the open channel junction velocity with higher accuracy than the genetic programming model.

Kumar *et al.* (2016) performed this study at Kopili river, India. Prediction for suspended sediment was done by use of soft computing techniques in which hydro-meteorological variables were taken as input parameter Models were developed with ANNs, radial basis function, least square support, vector regression, multi-linear regression and decision tree models which were mainly classification and regression tree and M5 model tree. Results obtained were evaluated through correlation coefficient, coefficient of efficiency, root mean square error, standard deviation ratio

etc. results showed that least square Support, vector regression and ANN models were three main soft techniques which gave much better results than all other techniques employed for assessing performance. In M5 model, linear regression function was fitted to data due to which a continuous representation of output data was achieved. M5 model analysis during its performance trial was much accurate in comparison to other like regression tree and multi- linear regression techniques.



*Materials
and
Methods*



3. MATERIALS AND METHODS

This chapter deals with description of study area, collection of hydrologic data, methodology adopted for suspended sediment concentration modelling using artificial neural networks, models calibration and validation and various statistical indices used for computing effectiveness of the developed models.

3.1 Description of the Study Area

3.1.1 Location

The Baitarani river originates from the Guptaganga hills ranges near Mankarancho village and flows eastward and joins the Bay of Bengal. Major portion of Baitarani river catchment lies in the state of Odisha and a small part of the upper reach falls in Jharkhand. The total area of Baitarani river basin is 10982 sq. km in which 10246 sq. km and 736 sq. km area are situated in Odisha and Jharkhand states, respectively. The catchment area is shown in Fig. 3.1.

The Baitarani river basin is located between $85^{\circ}10'$ to $87^{\circ}03'$ east longitudes and between $20^{\circ}35'$ to $22^{\circ}15'$ north latitudes. The basin is surrounded by the Brahmani on the South and West side, the Subernarekha on the north side, the Burhabalang and the Bay of Bengal on the east side.

3.1.2 Climatic conditions

Keonjhar district situated in the middle of the Baitarani river basin, the recorded maximum temperature is 48.5°C in summer and minimum 6°C in winter. Most of the rainfall in the watershed is received from the South-West monsoons from June to September. About 80% of annual rainfall occurs during June to September. The maximum and minimum annual rainfall is 3094 mm and 642 mm, respectively, and average rainfall is 1187 mm. Uneven rainfall are caused mostly due to depression in Bay of Bengal during the monsoon season. The maximum and minimum humidity are 83.08% and 39.63% in the months of April/May and August/September respectively on an average.

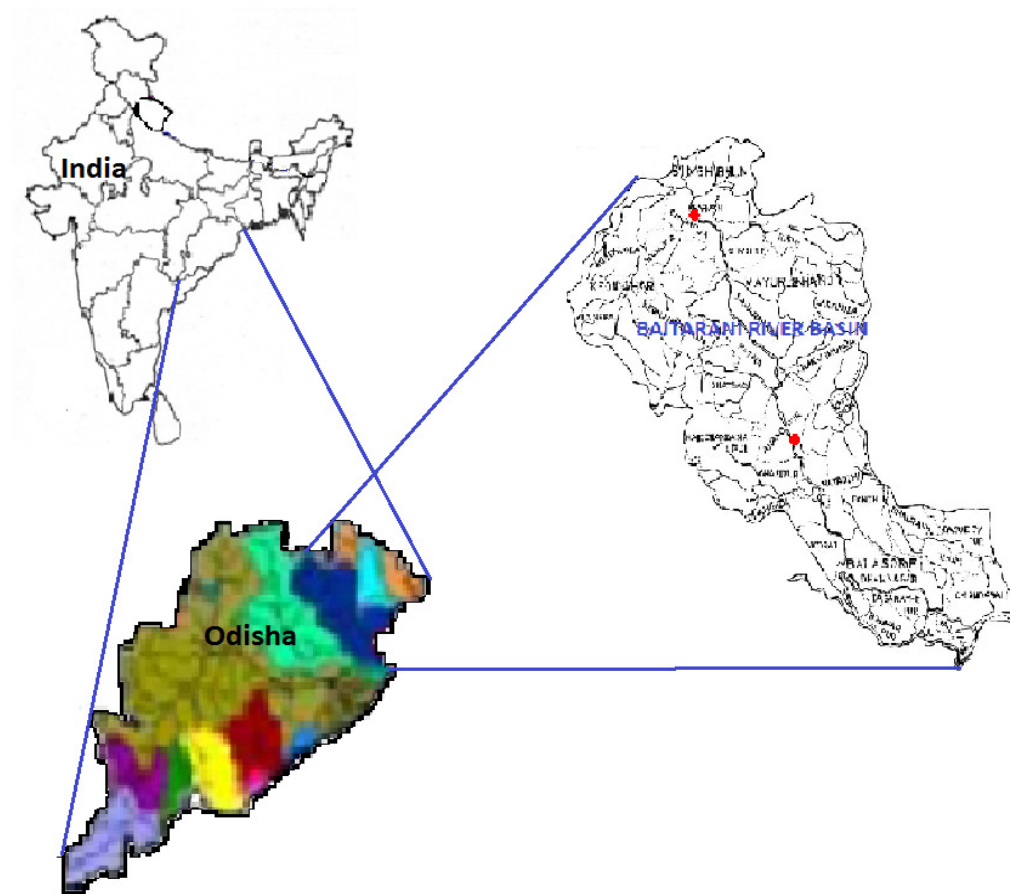


Fig. 3.1 Location map of Baitarani river basin

3.1.3 Geological and topographical characteristics

The geological features of upper Baitarani river basin have two main series- the iron ore series and the younger kolhan series. The iron ore series are represented by mica, hornblende, schist, bornblende, gneiss, phyllite, chert and jasper which along with singhbhum granite constitute the surrounding country rock. The kolhan series comprises mainly flat bedded kolhan, sand stone and conglomerate. The sand stone usually forms the flat topped hills over the peneplain granite terrain in this area. The generalized geological set up for whole of south Singhbhum and Keonjhar district is new dolerite, kolhan series, singhbhum and iron ore series.

The upper Baitarani river basin is of extreme nature, the middle Baitarani basin is partly hilly and partly plain and the lower Baitarani basin in coastal area. The Baitarani River originates at an elevation of 900 m from mean sea level (MSL) from the near Mankarancho village. The Keonjhar district of Odisha covers the major

portion of the basin area whereas Mayurbhanj, Sundargarh, Dhenkanal, Cuttack and Balasore districts cover the rest. The river flows in northern direction for about 80 km initially and then takes a sudden right angled turn and serves as a boundary between Bihar and Odisha states for a certain length that is up to the confluence of Kongira River.

There are 64 tributaries of Baitarani river, out of which 35 join the river on the left side and 29 join the river on the right side. The main tributaries are Kangira, Khairi Bandhan, Deo, Kanjhari, Sita, Kusei, and Salandi. The river after traversing in hilly regions enters the plains at Anandpur. Further below it meets the deltaic region at Akhuapada where it branches off and bifurcates. Further below it meets the river Brahmani and assumes the name Dhamra and joins the Bay of Bengal. The elevation at Champua is 367 m whereas at Anandpur is 28 m.

3.1.4 Soil characteristic and land use pattern

Red and yellow soils, red sandy and loamy soils are found in the Baitarani watershed mixed red and black soils and coastal alluvium. The trend of irrigation has undergone changes since 1978-79 due to construction of medium and minor irrigation projects. The technique of modern agriculture systems with application of chemical, fertilizers, pesticides and use of tested seeds has not been widely practiced in this basin, as such coupled with lack of irrigation facilities the yield of food grains is coming much less than the average.

Out of 831 thousand hectares of geographical area of Keonjhar district, 307 thousand hectares come under net area sown and 249 thousand hectares come under forest coverage. The net area sown and forest area are 37% and 30% of total area. These figures of Keonjhar district give an idea of the land coverage of the basin as it covers 60% area of the basin. Total area under forest is 40% of the basin.

3.2 Collection of Hydrologic Data

The hydrological data were collected from Divisional office of CWC Bhubaneswar, India. The collected hydrological data include daily discharge and daily suspended sediment concentration, for a period of 30 years (1977 to 2006). The daily data are recorded at two gauging stations- Champua and Anandpur located at Baitarani River. The longitude, latitude and drainage area upstream of Champua

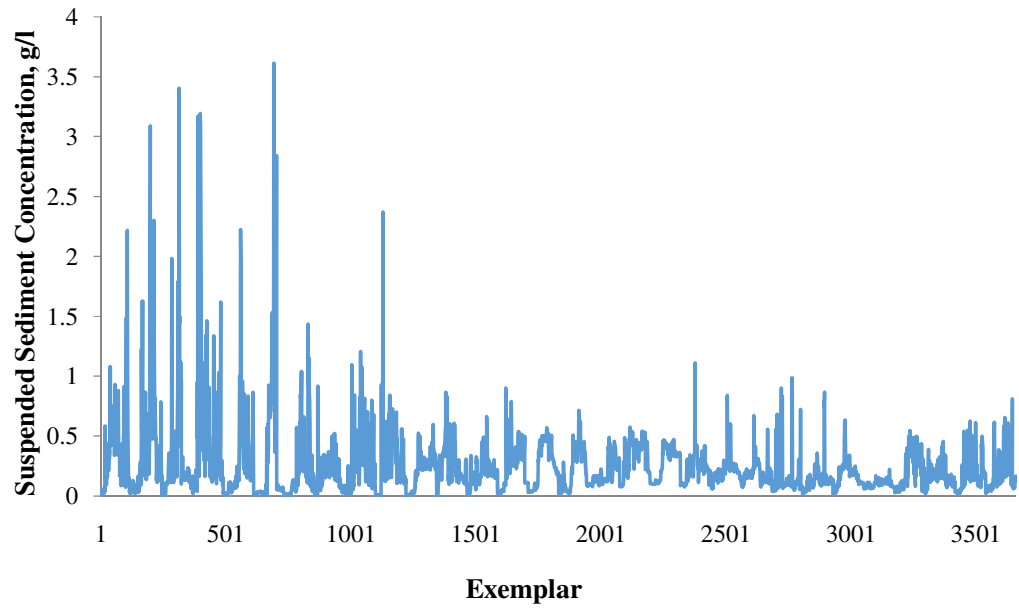


Fig. 3.2 Daily suspended sediment concentration for monsoon season from 1977 to 2006 at Champua station on Baitarani river

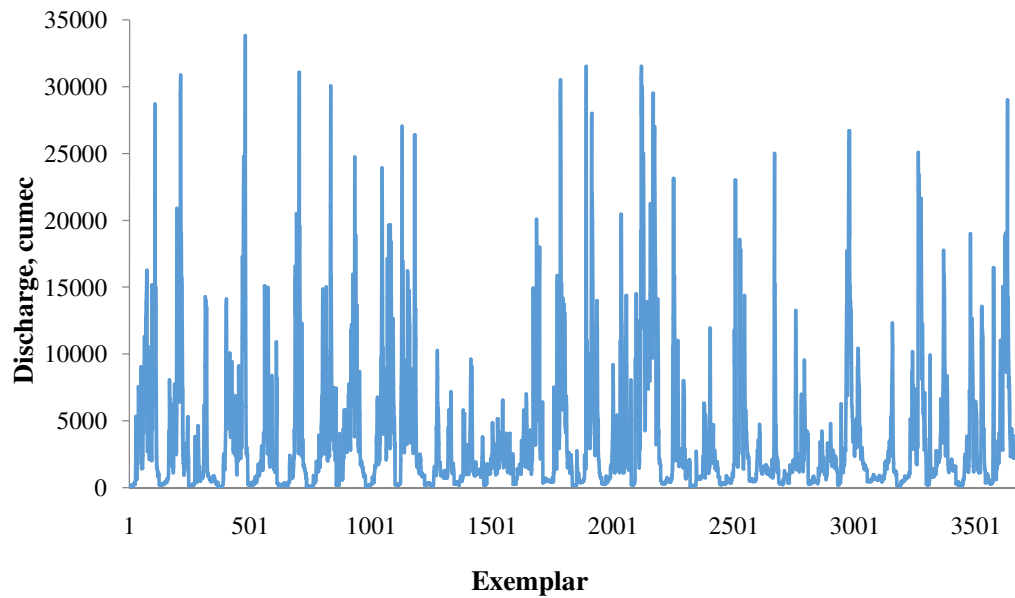
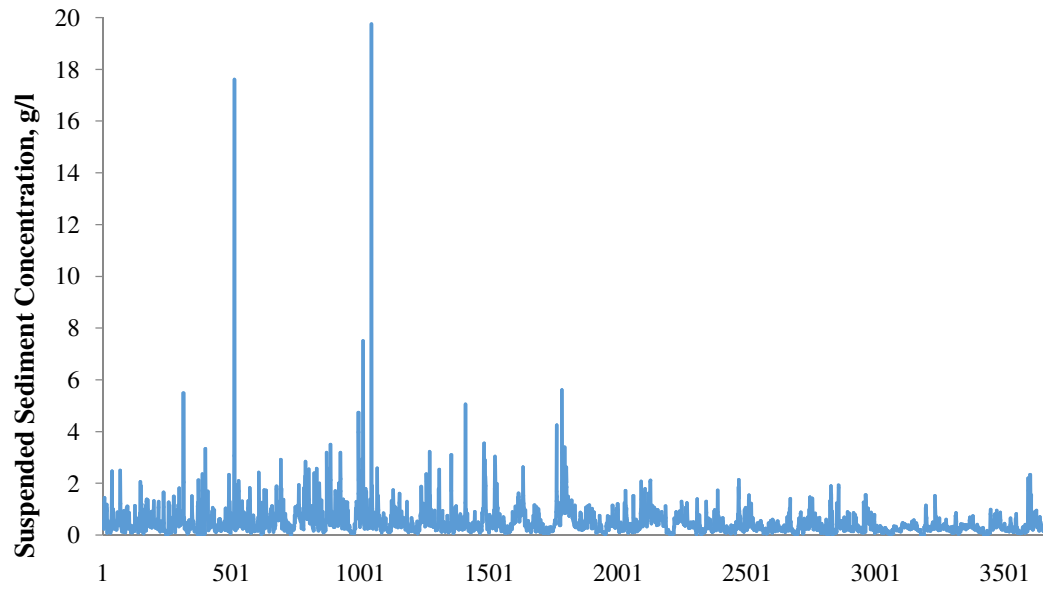
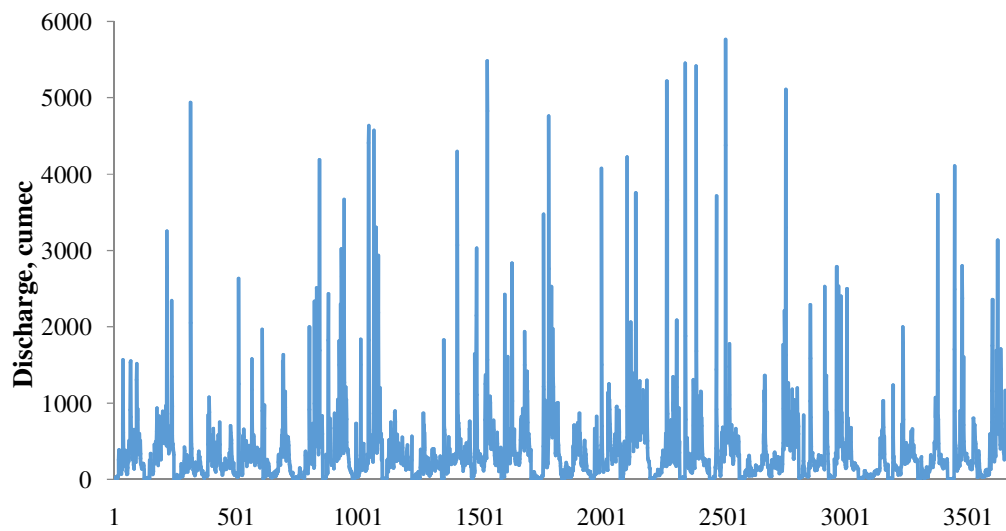


Fig. 3.3 Daily discharge for monsoon season from 1977 to 2006 at Champua station on Baitarani river



Exemplar

Fig. 3.4 Daily suspended sediment concentration for monsoon season from 1977 to 2006 at Anandpur station on Baitarani river



Exemplar

Fig. 3.5 Daily discharge for monsoon season from 1977 to 2006 at Anandpur station on Baitarani river

station are $85^{\circ}40'56''$, $22^{\circ}03'57''$ and 1710 sq. km, respectively. The longitude, latitude and drainage area upstream of Anandpur gauging station are $86^{\circ}07'23''$, $21^{\circ}12'34''$ and 8570 sq. km, respectively.

In this study, the daily data of monsoon season (1st June to 30th September) of runoff and suspended sediment concentration of Baitarani river is selected. Daily suspended sediment concentration and daily discharge at two stations- Champua and Anandpur are shown in Fig. 3.2, Fig. 3.3, Fig. 3.4 and Fig. 3.5, respectively.

3.3 Artificial Neural Networks

The original concept of an artificial neural networks or neural networks was developed by Warren McCulloch and Walter Pitts (1943). ANNs are built from number of different nonlinear processing elements which are known as “neurons” each of which receives connections from other neurons or and itself according to the training algorithm. The signals which are flowing on the connections are scaled by adjustable parameters known as weights (Principe *et al.*, 2000). Artificial neural work are inspired by structure of human brain, that is well suited for complicated task in hydrologic system too such as evaporation modelling, rainfall modelling, river flow modelling, suspended sediment yield modelling etc. ANNs have been proven to provide better solution for estimation of suspended sediment yield. The description of ANNs can only be accomplished by the description of biological neurons.

3.3.1 Structural description of artificial neural networks

ANN structures, broadly classified as recurrent (involving feedback) or non-recurrent (without feedback), have number of processing elements (also called neurons, neuroses) and connections. The basic structure of artificial neural network which is shown in Fig. 3.6 can be broadly divided into three layers;

- 1) **Input layer-** The layer at the bottom is known as input layer or input neuron network. The nodes of input layer are not neurons but nodes of rest of the layers are neurons. In the Fig. 3.6 x_1 , x_2 , x_3 , x_4 and x_5 are input layer nodes.
- 2) **Hidden layer-** The layer between input and output layer is known as hidden layer where the knowledge of past experience is saved.

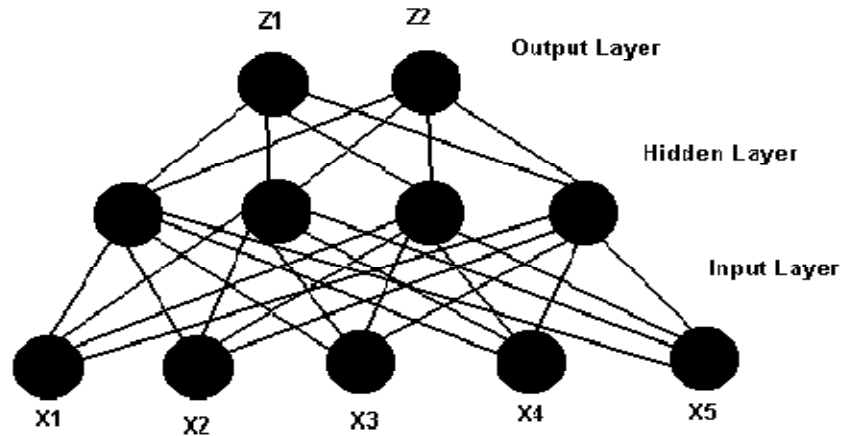


Fig. 3.6 Basic structure of ANNs

3) Output layer- The layer at the top which gives the output is known as output layer. In the Fig. 3.6 z_1 and z_2 are output layer neurons.

3.3.1.1 Perceptron

Perceptron is the heart of every Neural Network (also called processing element) which is analogous to the neuron nucleus in the brain. The second layer, the very first hidden layer, is known as perceptron. Input signals are applied to the node via input connection. The connections have “strength” which changes as the system learns. How strongly one neuron influences those neurons connected to it, is called “connection strength”. The strength of the connections are called to as weights or “connection weights”.

Mathematically signals values coming from input layer are multiplied by the value of those particular weights. In general, the input of node x_i is multiplied by the weight of the connection w_i between nodes x_i and b to produce the input signal to node b . Weights are stored in local memory of nodes and hold the long-term memory of the network. At the perceptron all weighted input are summed. This sum value is then passed to a scaling function. The selection of scaling function is part of the neural network design.

The function of the ANNs is to map a set of inputs to a set of outputs. A perceptron is shown in Fig. 3.7. Let x_i ($i = 1, 2, \dots, m$) are inputs and w_i ($i = 1, 2, \dots, m$) are respective weights. The net input to the node is given as;

$$net = \sum_{i=1}^n x_i w_i \quad \dots (3.1)$$

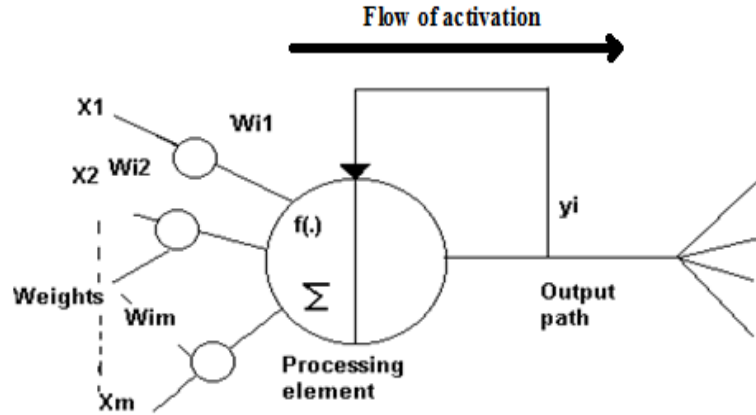


Fig. 3.7 Structure of the perceptron

The net input then goes through activation function f and then the output y of the node is computed as-

$$y = f(net) \quad \dots (3.2)$$

3.3.1.2 Network architectures

Out of the three network architectures in ANNs (i.e. single-layer feedforward networks, multilayer feedforward networks and recurrent networks), the multilayer feedforward network was used in this study. The model is discussed given below;

Multilayer feedforward networks

One or more hidden layers are present in the multilayer feedforward neural networks. Its computation nodes are known as hidden neurons. The hidden layer intervenes between the input and the output in some useful manner. The network has the capability to take higher-order statistics by increasing one or more hidden layers, which is particularly valuable when the input layer has a large size. According to Churchland and Sejnowski (1992), the neural network obtains a global perspective, though it has local connectivity due to the extra set of synaptic connections.

The nodes where computation occurs are called computation nodes or neurons. There is no computation in the input layer, so the nodes of the input layer are

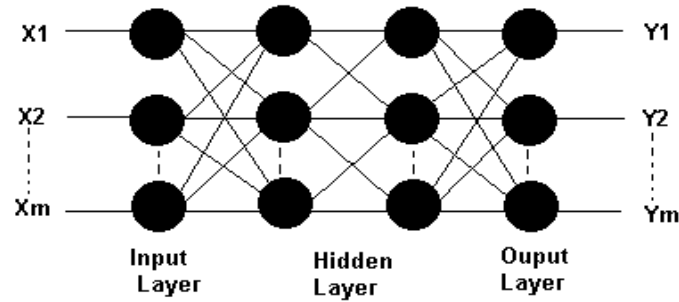


Fig. 3.8 Multilayer feedforward networks

not the neurons. The input layer nodes which are source nodes of the neural network supply and elements of the activation pattern are called input vector, which constitute the input signals applied to the neurons in the second layer. The second layer output signals are used as input signals to the third layer, and so on for the rest of the network. The architectural graph in Fig. 3.8 illustrates the layout of a multilayer feed forward neural network for the case of two hidden layers.

3.3.2 Learning processes of artificial neural networks

The determination of its weight matrix training is one of the important steps in development an ANN model. There are two types of training or learning mechanisms i.e. supervised and unsupervised. When a set of input pattern and its known output pattern is used to train the neural network, this type of learning is called supervised learning. In this learning an external teacher or user finds the error between computed output and observed output during the training of network and this error is used to make adjustments in the connection weights among nodes of different layers to minimize the error. Supervised learning is used for classification, functional mapping etc. When there is no teacher present to train the patterns, such type of learning is called unsupervised learning. In unsupervised learning the system learns on its own by finding regularities in the input space with the help of correlation and without direct feedback from the teacher or user

In this study, supervised learning is used. There are several algorithms for supervised learning. Among these algorithms, back-propagation is the popular due to its simplicity and effectiveness. The back-propagation algorithm has emerged as the workhorse for the design of an MLP. MLP is completed by using a back propagation algorithm that involves forward phase and backward phase.

3.3.2.1 Back propagation algorithm

In the back-propagation algorithm, the network weights are modified by minimizing the error between estimated value and observed values. Back-propagation is an iterative learning process in which all weight of parameters are randomly initialized and after that updated (in each iteration) through feed-forward calculations and back-propagation of errors which are described below;

1) Feed-forward calculations

The input layer nodes receive the input signals which are passed to the hidden layer or layers and then to the output layer of the network in feed forward calculation. The signals are, then multiplied by the current values of connection weights, and then the weighted inputs are added to yield the net input to each neuron of the next layer and then net input of a neuron is passed through a transfer function to produce the output of the neuron. Directions of signal flow and error propagation in an artificial neural network are shown in Fig 3.9.

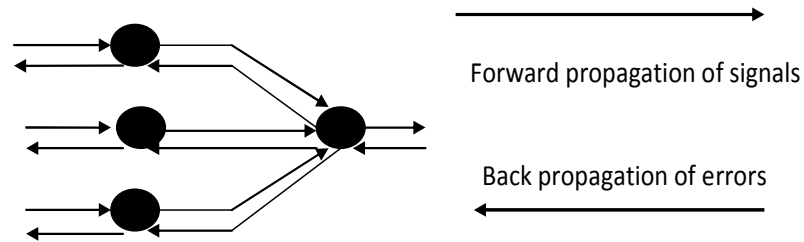


Fig. 3.9 Directions of signal flow in an ANNs

In different layers of neural network for feed forward calculations, the procedure is as follows;

The net input to j^{th} node is given by-

$$neth_j = \sum_{i=1}^{ni} wh_{ji} x_i \quad \dots (3.3)$$

Where, ni is the number of neurons in the input layer and wh_{ji} is the connection weight between i^{th} node of the input layer of network and j^{th} neuron of the hidden layer. The output of j^{th} node of the hidden layer h_j is given by;

$$h_j = f(neth_j) \quad \dots (3.4)$$

The net input to k^{th} node is given by;

$$nety_k = \sum_{j=1}^{nh} wo_{kj} h_j \quad \dots (3.5)$$

Where, nh is the No. of neurons in the hidden layer and wo_{kj} shows connection weight between j^{th} node of the hidden layer and k^{th} node of the output layer of networks. The output of k^{th} node is given by;

$$y_k = f(nety_k) \quad \dots (3.6)$$

The error calculated at the output layer is sent back to the hidden layers and then passed on to the input layer, so that updates for the connection weights are determined the sum square error E , is given by;

$$E = \frac{1}{2} \sum_{k=1}^{no} (y_k - t_k)^2 \quad \dots (3.7)$$

Where, t_k is the observed output or output desired at the k^{th} neuron and y_k is the calculated output at the same neuron. Weights are updated and changed from their old values to minimize the error. The learning process starts with a random set of weights. Weights are updated through error back-propagation during the training process, in order to reach better efficient weights and speed of learning process it arise many types of back propagation.

2) Error back-propagation

The error calculated at the output layer of is returned back to the hidden layers and then to the input layer, to decide the updates for the weights. This method is derived from the well-known gradient descent method in which the weights updating are performed by moving in the direction of negative gradient along the multidimensional surface of the error function. The learning process starts with a random set of weights. During the training process, weights were updated through error back-propagation using appropriate relationship for output and hidden layers. The back propagation algorithm reduces the error function in weight space using the method of gradient. The combination of weights which reduces the error function is considered to be a solution of the learning problem.

3.3.2.2 Activation functions

The activation function or transfer function is a mathematical formula which used to find out the output of a processing element. The activation function is a

relationship between the internal activation level of the neuron and the outputs. The connections between the input layer and the middle layer contain weights as determined by training the system. The hidden layer sums the weighted inputs are summed up by the hidden layer.

The activation functions of a node define the output of that particular node given an input/inputs. An activation function chooses the best processing element by using the trial and error method. The most commonly used activation functions in hydrology for best applications are sigmoid and hyperbolic tangent. In the present study, sigmoid activation function is used. A sigmoid axon function is a mathematical function having as S shape (sigmoid curve) as shown in Fig. 3.10 and defined by the Equation 3.10.

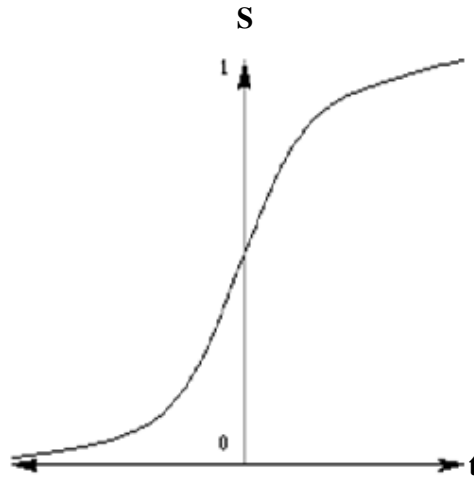


Fig. 3.10 Sigmoid axon function

A set value based upon which the final output of the network is calculated, is called “threshold”. The threshold value is used in the activation function. A comparison is made between the calculated net input and the threshold to obtain the network output. For each and every application, there is a threshold limit. If output range of the activation function is from -1 to +1, the activation function using threshold can be defined by the Equation 3.8 and 3.9.

$$net\ f = 1\ \text{if}\ net \geq 0 \quad \dots (3.8)$$

$$net\ f = -1\ \text{if}\ net < 0 \quad \dots (3.9)$$

$$S(t) = \frac{1}{1 + e^{-t}} \quad \dots (3.10)$$

3.3.2.3 Learning algorithms

In the learning process, learning or training algorithm is updating network parameters to achieve a desired model performance based on a set of training data. A training rule defines how exactly the network weights should be updated between successive epochs. In addition, each layer has an associated learning rule and learning parameters. The number of processing element and learning parameters are entered in the corresponding fields. The learning rule is the means through which the correction term is specified. If the learning rate is very small, then it takes a long time. If it is set very high, then the adaptation deviates and the weights can not be used.

The learning algorithm is used to calculate the adjusted weights and biases of the network so that the error between computed and observed output is minimized. In more recent studies the L-M algorithm is being used due to its higher efficiency and high convergence Speed. L-M algorithm was shown to be more efficient than the CG and GDX algorithms (Solaimani, 2009). Many other researchers have also proved the efficiency of L-M algorithm. A specialized back propagation optimization technique known as Levenberg-Marquardt Back propagation developed by Hagan and Menhaj (1994) was used in the study to train the MLP-ANN. That is, the synapse weights were optimized to find the best simulation performance within the training period. Training the ANNs was aimed at minimizing the mean squared optimization. For neural network training the objective function is the minimizing the error function.

$$\Delta W = (J^T J + \mu I)^{-1} J^T e \quad \dots (3.11)$$

Where, J , the Jacobian matrix, e is the error vector, Δw is increment of weights, T shows the target output and μ is the parameter changed or learning rate.

3.4 Model Development

Prior to development of models, standardization of raw data and input-output variables identification was carried out.

3.4.1 Standardization of raw data

In most of the cases raw data values range between a minimum and a maximum value, differing significantly from one variable to the other, to avoid the possibility of a model from giving more importance to some variables as compared to others, data is standardized between certain constant values such as 0 to 1 or -1 to +1 (Rai and Mathur, 2008). In this study, data has been standardized between 0 to +1 using the Equation 3.12.

$$x' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \dots (3.12)$$

Where, x' is the standardized value if the raw data value x , x_{max} and x_{min} are the maximum and minimum values of raw data value x respectively.

3.4.2 Identification of input and output variables

Input variables selection is a crucial step for model forecasting as they decide the structure of the ANNs model and affect output of model. The current day suspended sediment is not only dependent on the stream flow of the current time but also on the runoff and suspended sediment of the previous periods (Cobaner *et al.*, 2009). Therefore, present day suspended sediment concentration is the considered as the function of discharge and suspended sediment concentration of the previous days along with the present day discharge. So the number of input variables depends on the lag time. Several combinations of the discharge and suspended sediment concentration were tried to construct the proper input structure. The present day suspended sediment concentration is supposed to be a function of discharge of present day and previous n days lag discharge along with previous n days lag suspended sediment concentration.

3.4.3 Development of artificial neural networks models

After the identification of input and output variables, various artificial neural networks models were developed for both the stations i.e. Anandpur station and Champua station, by using various combinations of Equation 3.12 and the developed models for ANNs are listed in Table 3.1.

Table 3.1 List of various ANNs models for Baitarani river basin

Model	Output-input variables
M-1	$S_t = f(S_{(t-1)}, Q_t)$
M-2	$S_t = f(S_{(t-1)}, Q_t, Q_{(t-1)})$
M-3	$S_t = f(S_{(t-1)}, S_{(t-2)}, Q_t, Q_{(t-1)})$
M-4	$S_t = f(S_{(t-1)}, S_{(t-2)}, Q_t, Q_{(t-1)}, Q_{(t-2)})$
M-5	$S_t = f(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, Q_t, Q_{(t-1)}, Q_{(t-2)})$
M-6	$S_t = f(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, Q_t, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)})$
M-7	$S_t = f(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, S_{(t-4)}, Q_t, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)})$
M-8	$S_t = f(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, S_{(t-4)}, Q_t, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)}, Q_{(t-4)})$

Where, S_t is d present day suspended sediment concentration, $S_{(t-1)}$ is the one day lag suspended sediment concentration, $S_{(t-2)}$ is the two days lag suspended sediment concentration, $S_{(t-3)}$ is the three days lag suspended sediment concentration and $S_{(t-4)}$ is the four days lag suspended sediment concentration, Q_t is the present day discharge, $Q_{(t-1)}$ is the one day lag discharge, $Q_{(t-2)}$ is the two days lag discharge, $Q_{(t-3)}$ is the three days lag discharge and $Q_{(t-4)}$ is the four days lag discharge.

3.4.4 Training and testing of MLP-ANNs models

For successful modeling, training and testing data is to be selected. So, the data was divided into two parts i.e. training and testing data. Testing data sets are used for evaluation of model validity because; after some point during the training process over fitting is likely to occur. Use of test data sets prevents over training of models at different iterations by checking the performance. For system to be modeled efficiently, the number of training data sets should contain all the possible combinations of events.

Discharge and suspended sediment concentration data are represented as Q_{ij} and S_{ij} respectively for i th year and j th day. For training and testing of the ANNs, the required daily discharge time series Q_{ij} for $i = 1$ to M year and $j = 1$ to N day index

was available, where M and N are total number of years and total number of days respectively. Since the data was used only for monsoon season (1st June to 30th September) for a period of thirty years (1977 to 2006), the value of N was found to be equal to 3660 days and value of M was found to be equal to 30 years. Data accounting from year 1977 to 1996 was used for model calibration and data accounting from year 1997 and 2006 was used for model validation for both the stations i.e. Anandpur and Champua.

In this study, the training of ANNs models was done by using back propagation algorithm for the minimum error function, single and double hidden layers neural networks, processing elements in architecture are found by trial and error procedure, in this study processing elements varies from 1 to 10 in both the hidden layers simultaneously, sigmoid activation function, Levenberg -Marquardt learning rule, maximum 1000 number of epochs and 0.001 training threshold assigned as per ANN model. The best model was chosen by considering the error generated by the system. A model is considered to be best when it generates very minimum error.

3.5 Performance Evaluation of Models

Performance measures are used to indicate how well a model performs its tasks. The performance of the model can be measured qualitatively and quantitatively. Qualitative assessment is one of the simplest methods of model evaluation and is based on the visual observations. This consists of visual observations based on graphical comparison between observed and the predicted values. Since the visual observations are subjected to personal bias as the observations may vary from person to person, qualitative analysis is not considered to be a reliable technique for performance evaluation. Quantitative evaluation, on the other hand, is considered to be effective in performance evaluation of the models. The different performance evaluating indices based on quantitative evaluation which were used in this study for predicting the effectiveness of the models are discussed as under;

3.5.1 Mean Square Error (MSE)

The mean square error (MSE) is determined to measure the prediction accuracy. It always produces positive values by squaring the errors. Its range is from 0 to ∞ . The MSE is zero for perfect fit and increased values indicate higher discrepancies between computed and observed values (Wilks, 1995). The mean

square error between measured and computed values is determined by the following equations;

$$MSE = \frac{\sum_{i=1}^N (S_{oi} - S_{ci})^2}{N} \quad \dots (3.13)$$

Where, N is the total number of observations or data in the training or testing data set and S_{ci} and S_{oi} are the computed and measured suspended sediment concentration for i^{th} observations.

3.5.2 Normalized Mean Square Error (NMSE)

The normalized mean square error is given by following equation;

$$NMSE = \frac{P N MSE}{\sum_{j=0}^P \frac{N \sum_{i=0}^N S_{cij}^2 - \left(\sum_{i=0}^N S_{cij} \right)^2}{N}} \quad \dots (3.14)$$

Where, P is the number of output processing elements, MSE is mean square error, N is the total number of observations in the training/testing data set and S_{cij} is the computed output for i^{th} observations and at j^{th} processing element.

3.5.3 Root mean square error (RMSE)

Root mean square error is the mostly used statistical index to evaluate the difference between observed values and computed values of the models. The range of RMSE is from 0 to ∞ . The root mean square error is zero for perfect fit model and increased values indicate higher discrepancies between measured and computed values. The root mean square error is computed with the help of following equation;

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (S_{ci} - S_{oi})^2}{N}} \quad \dots (3.15)$$

Where, S_{ci} and S_{oi} are the computed and measured suspended sediment concentration for i^{th} exemplar and N is the total number of observations in the training or testing data set.

3.5.4 Correlation coefficient (r)

The correlation coefficient measures the correlation between the computed and the measured values i.e. the degree to which the observed and computed values are linearly related. The range of correlation coefficient is from -1 to +1. A positive correlation coefficient indicates that the observed and computed values tend to go up

and down together. If the variables go in opposite directions, it results in a negative correlation coefficient. It is computed by using the following equation;

$$r = \frac{\sum_{i=1}^N (S_{oi} - S_{om}) \sum_{i=1}^N (S_{ci} - S_{cm})}{\sqrt{\sum_{i=1}^N (S_{oi} - S_{om})^2} \sqrt{\sum_{i=1}^N (S_{ci} - S_{cm})^2}} \quad \dots (3.16)$$

Where, S_{ci} and S_{oi} are the computed and measured suspended sediment concentration for i^{th} observation, N is the total number of observations in the training or testing data set and S_{om} and S_{cm} are the mean of computed and observed suspended sediment concentration values.

3.5.5 Minimum description length (MDL)

Rissanen's minimum description length (MDL), similar to the AIC, combines the error of model with the number of degree of freedom to find out the level generalization. The goal here, is to minimize this term.

$$MDL(k) = N \ln(MSE) + 0.5 k \ln(N) \quad \dots (3.17)$$

Where, k is the number of network weights, N is the total number of observations in the training/testing data set.

3.5.6 Akaike's information criterion (AIC)

Akaike's information criterion (AIC) measures the trade off between training performance of the model and network size. The goal in this case is to minimize this term so that a network with the best generalization is produced.

$$AIC(k) = 2k + N \ln(MSE) \quad \dots (3.18)$$

Where, k is the number of network weights, N is the total number of observations in the training or testing data set and MSE is the mean square error.

3.5.7 Coefficient of efficiency (CE)

Coefficient of efficiency computes the goodness of fit between the measured and the computed values of a model. It is calculated using the following equation;

$$CE = 1 - \frac{\sum_{i=1}^N (S_{oi} - S_{ci})^2}{\sum_{i=1}^N (S_{oi} - S_{om})^2} \quad \dots (3.19)$$

Where, S_{ci} and S_{oi} are the computed and measured suspended sediment concentration for i^{th} exemplar, S_{om} is the mean of observed suspended sediment concentration values and N is the total number of observations in the training or testing data set.

It was suggested by Nash and Sutcliffe (1970), so it also called Nash-Sutcliffe efficiency. It can range from $-\infty$ to 1. An efficiency of 1 shows a perfect match between computed and measured values. An efficiency of 0 indicates that the model computed values are as accurate as the average of the measured data, whereas an efficiency less than zero shows that observed mean is a better computer than that of the model.



*Results
and
Discussion*



4. RESULTS AND DISCUSSION

This chapter deals with development and applications of artificial neural networks (ANNs) models to predict daily suspended sediment concentration for the Baitarani river at Anandpur and Champua using daily discharge and daily suspended concentration data of 30 years of monsoon period (1st June 1977 to 30th September 2006).

The performance of the developed models was evaluated qualitatively by visual observations and quantitatively by employing various indices viz. correlation coefficient (r), coefficient of efficiency (CE), mean square error (MSE), normalized mean square error (NMSE), minimum description length (MDL), root mean square error (RMSE) and Akaike's information criterion (AIC) for prediction of daily suspended sediment concentration of the Baitarani river.

4.1 Development of Daily Suspended Sediment Concentration Models

ANNs based daily suspended sediment concentration models were developed by using present day discharge (Q_t) along with the different combinations of previous days discharges ($Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$ and $Q_{(t-4)}$) and previous days suspended sediment concentrations ($S_{(t-1)}$, $S_{(t-2)}$, $S_{(t-3)}$ and $S_{(t-4)}$) for the prediction of present day suspended sediment concentration (S_t) for Baitarani river basin as given in Table 3.1. The observed data of first twenty years (1977-1996) were used for calibration of the developed models and the remaining ten years data (1997-2006) were used for validation of the developed models. Artificial neural networks based models were trained by using multilayer feedforward neural networks for maximum epochs of 1000 and threshold value of 0.001 with varying number of neurons from 1 to 10 in single and double hidden layer with sigmoid transfer function and L-M learning rule. The performance evaluation of daily suspended sediment concentration models at Champua station located at top and Anandpur station located at outlet of the Baitarani river basin are described below;

4.1.1 Qualitative performance evaluation of daily suspended sediment concentration models at Champua station

Qualitative assessment is one of the simplest methods of model evaluation and is based on the visual observations. This consists of visual observations based on

graphical comparison between observed and computed values. In this study, various artificial neural network architectures were applied using trial and error procedure and network architecture which were found to be best during testing and training periods at Champua station using qualitative evaluation are shown in Table 4.1.

Table 4.1 Best selected network architecture for models at Champua station

Model	Network architecture	No. of epochs ran
M-1	2-10-10-1	296
M-2	3-10-10-1	245
M-3	4-10-10-1	127
M-4	5-6-6-1	196
M-5	6-10-10-1	51
M-6	7-5-5-1	84
M-7	8-6-6-1	74
M-8	9-10-10-1	71

The observed and the computed suspended sediment concentration for artificial neural networks based models were compared graphically using sediment hydrographs and scatter plots during testing period because during training period the model performance can be improved by over fitting the data and that can not be consider under selection of best models but model performance during testing period is independent of this.

4.1.1.1 Performance evaluation based on sediment hydrographs

Sediment hydrographs for qualitative evaluation are plotted between observed and computed suspended sediment concentration values on ordinate and their corresponding occurrence time on abscissa and are shown in Figs. 4.1 through 4.8 for models M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8 during testing period at Champua station. It was observed from sediment hydrographs that out of eight models, M-3, M-6 and M-7 very closely predict the peaks accurately and rest of the models i.e. M-1, M-2, M-4, M-5 and M-8 over predict the peaks.

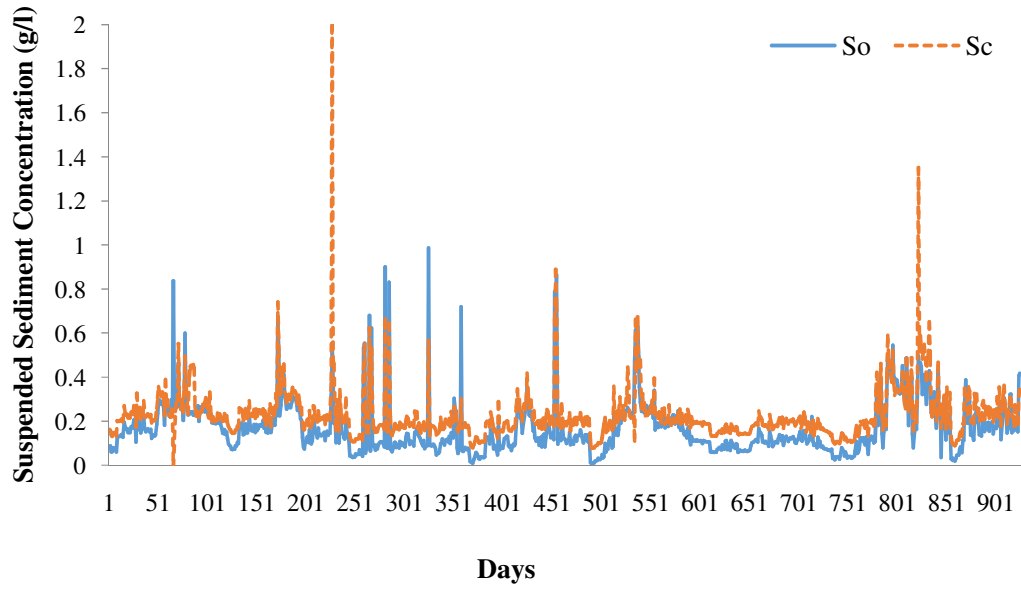


Fig. 4.1 Observed (So) and computed (Sc) suspended sediment concentration using M-1 model during testing period at Champua station

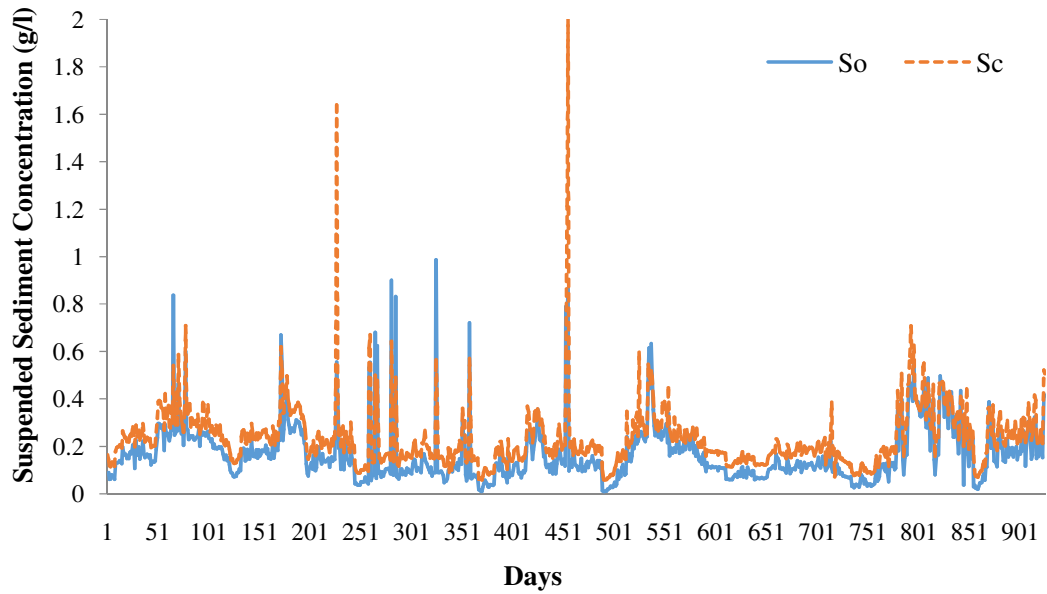


Fig. 4.2 Observed (So) and computed (Sc) suspended sediment concentration using M-2 model during testing period at Champua station

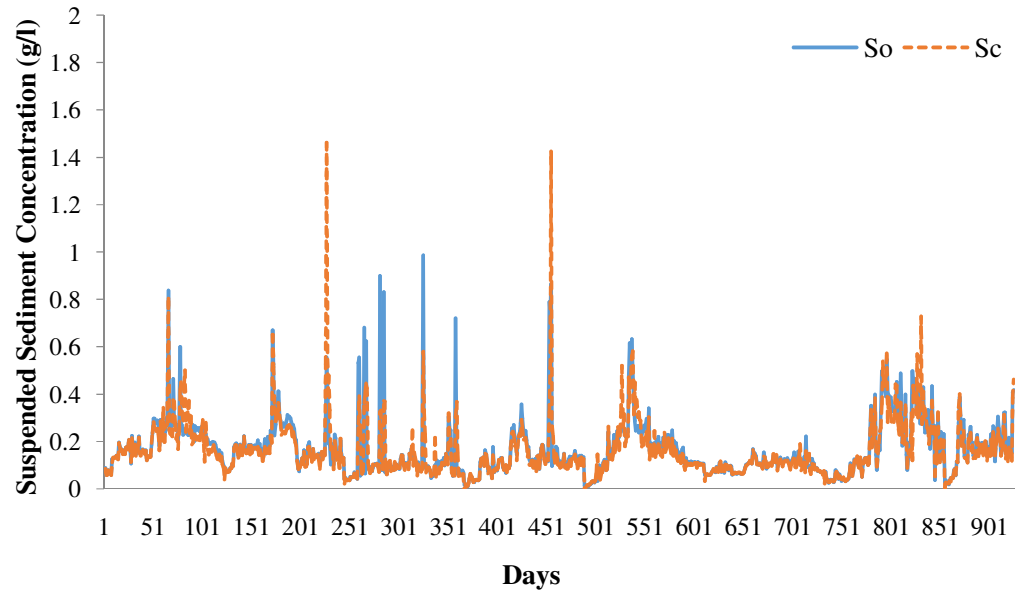


Fig. 4.3 Observed (So) and computed (Sc) suspended sediment concentration using M-3 model during testing period at Champua station

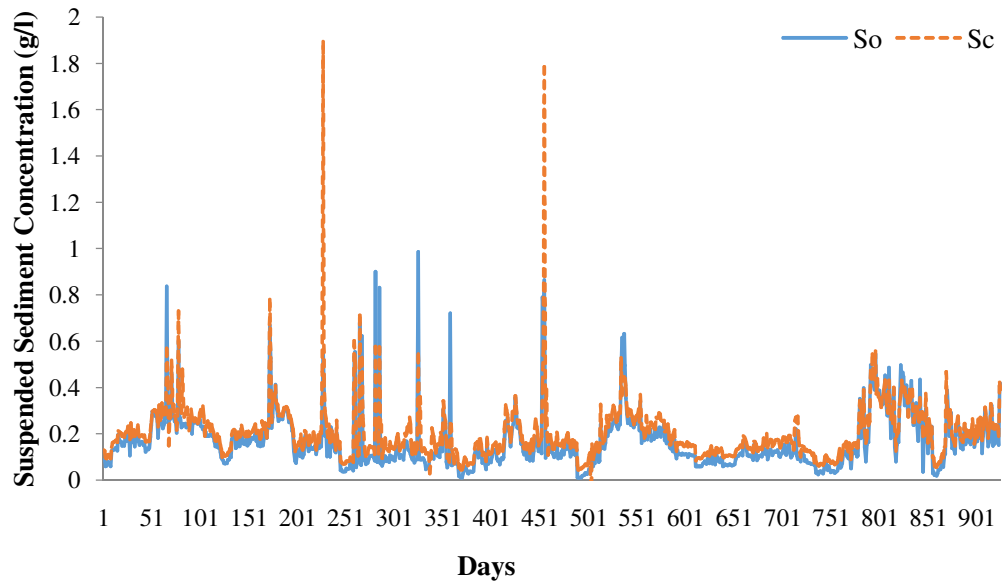


Fig. 4.4 Observed (So) and computed (Sc) suspended sediment concentration using M-4 model during testing period at Champua station

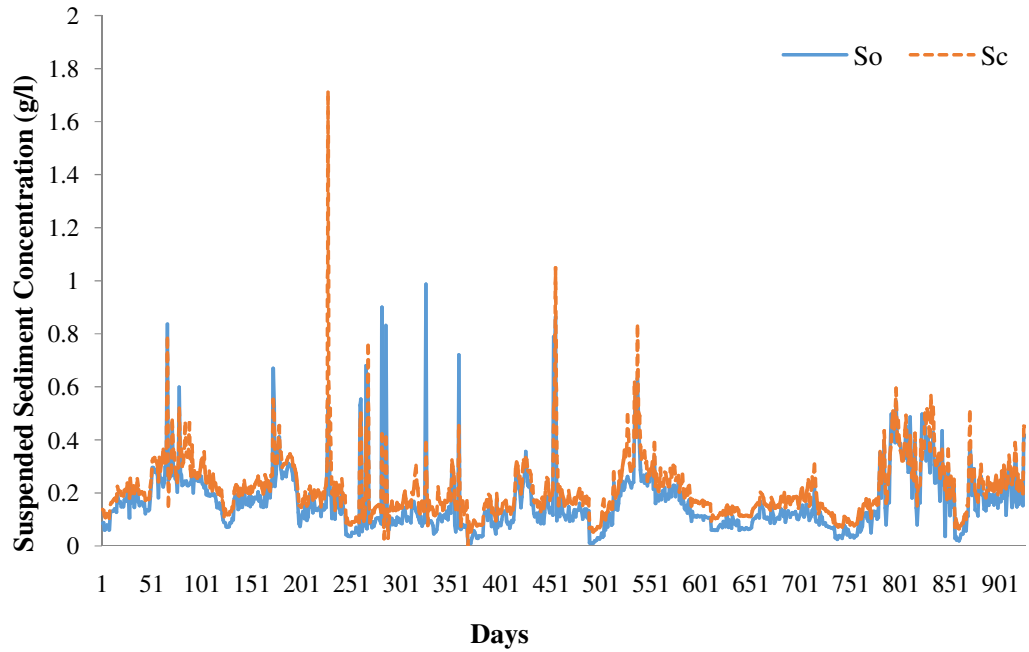


Fig. 4.5 Observed (So) and computed (Sc) suspended sediment concentration using M-5 model during testing period at Champua station

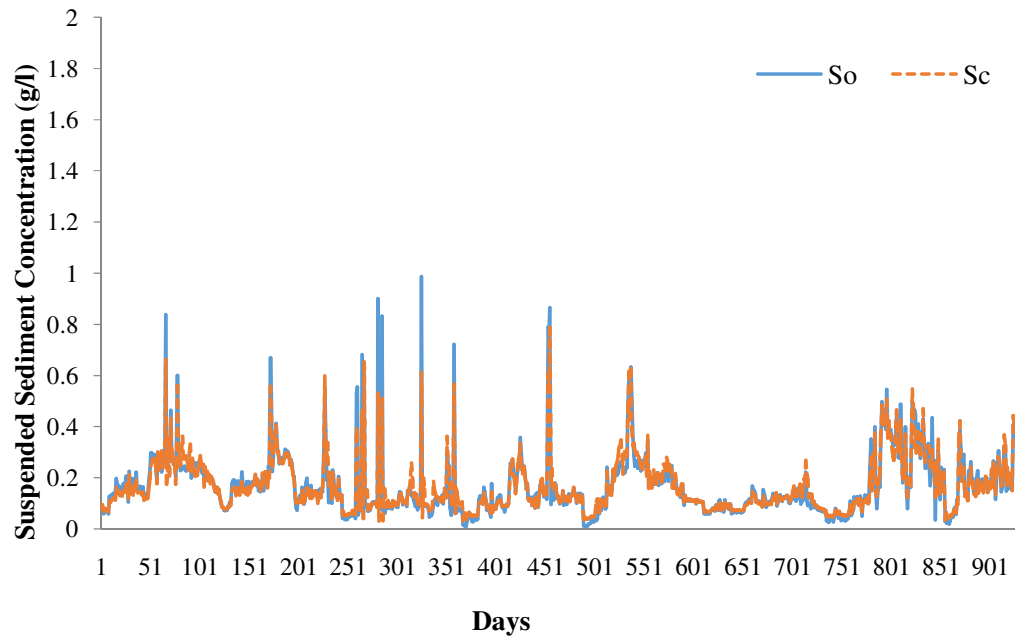


Fig. 4.6 Observed (So) and computed (Sc) suspended sediment concentration using M-6 model during testing period at Champua station

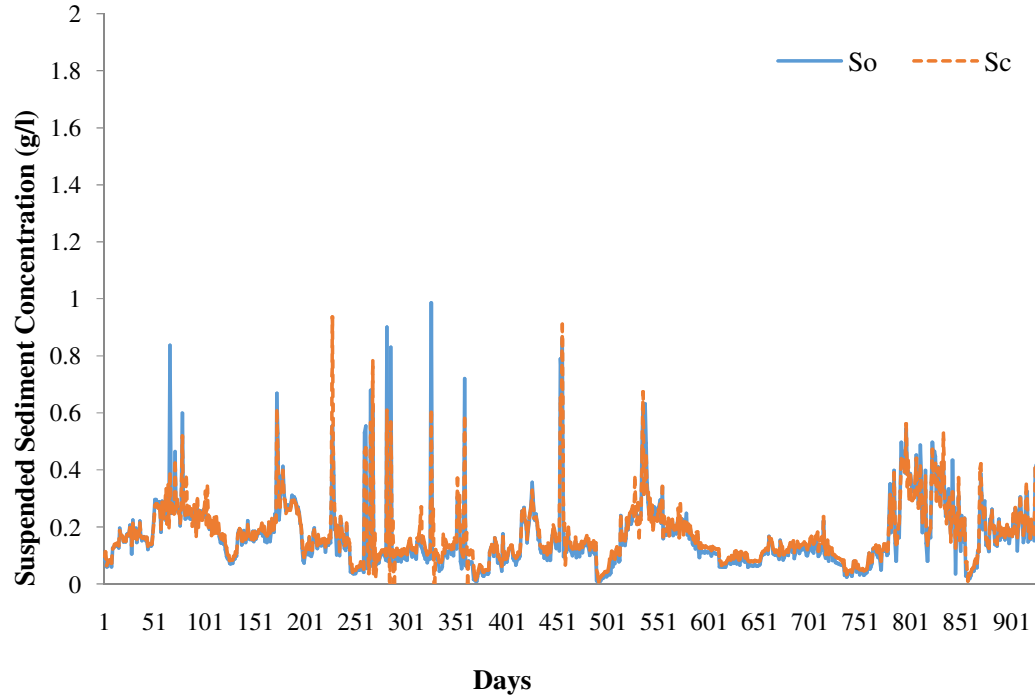


Fig. 4.7 Observed (So) and computed (Sc) suspended sediment concentration using M-7 model during testing period at Champua station

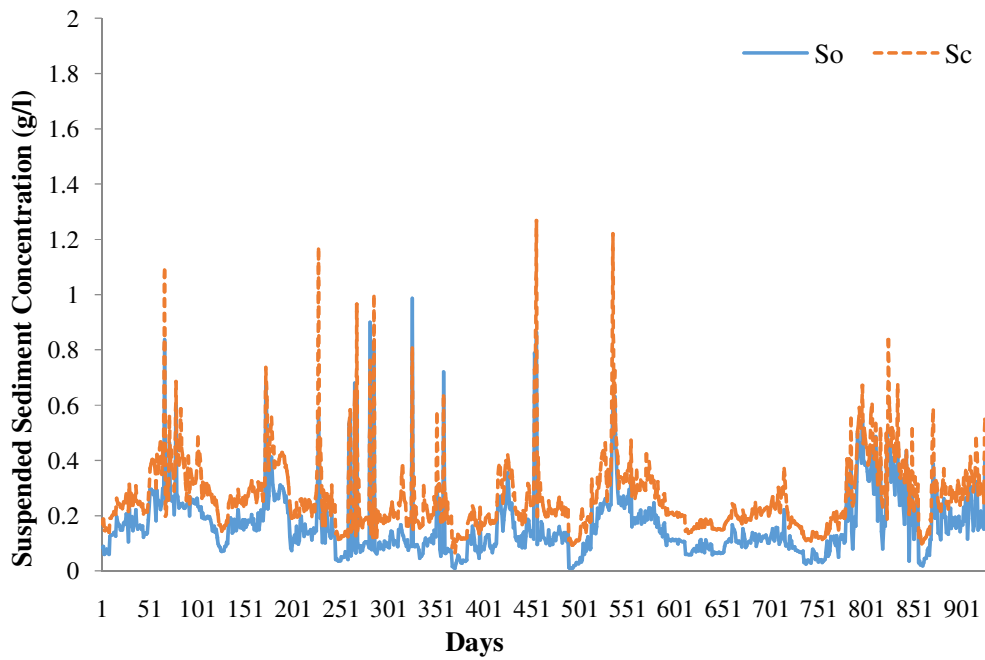


Fig. 4.8 Observed (So) and computed (Sc) suspended sediment concentration using M-8 model during testing period at Champua station

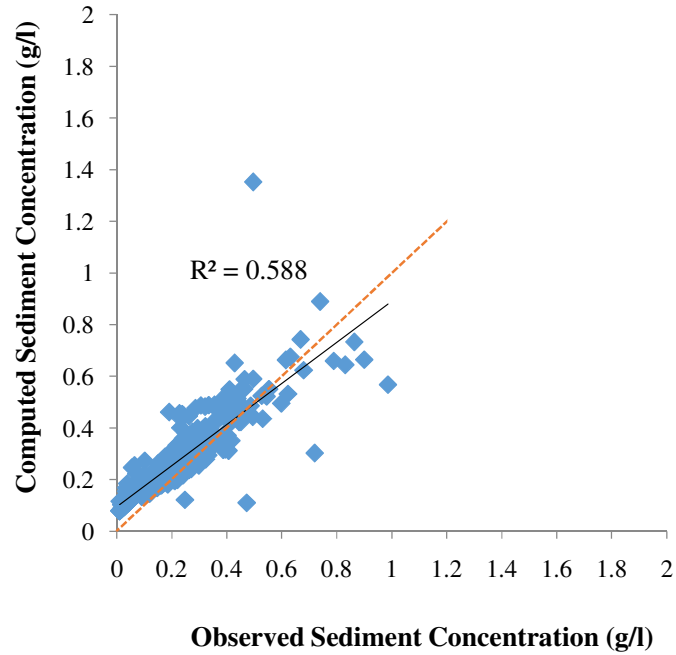


Fig. 4.9 Scatter plot of suspended sediment concentration using M-1 model during testing period at Champua station

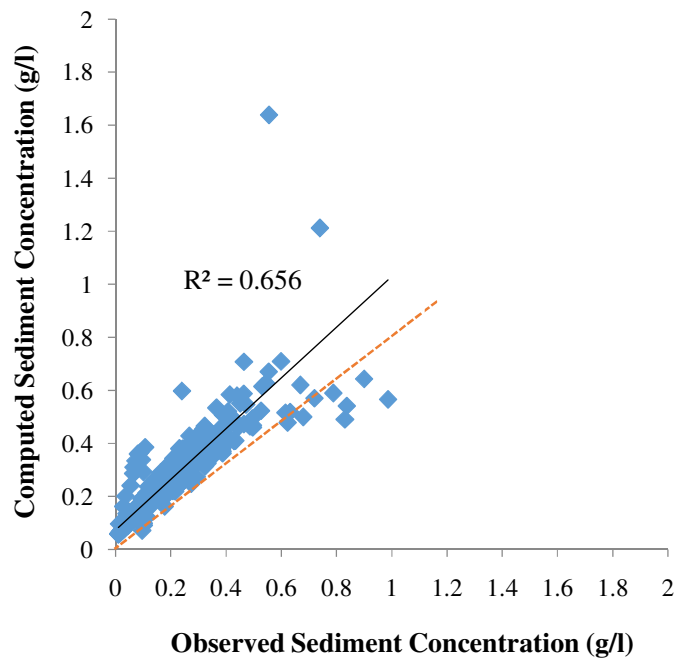


Fig. 4.10 Scatter plot of suspended sediment concentration using M-2 model during testing period at Champua station

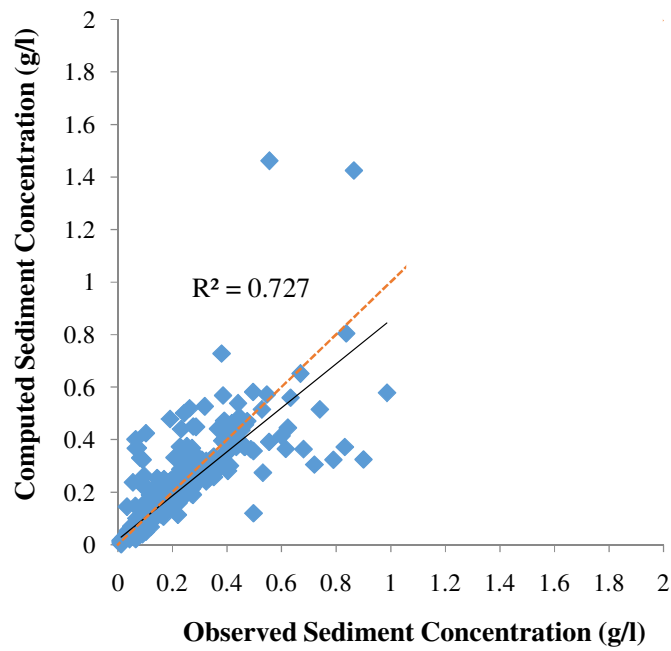


Fig. 4.11 Scatter plot of suspended sediment concentration using M-3 model during testing period at Champua station

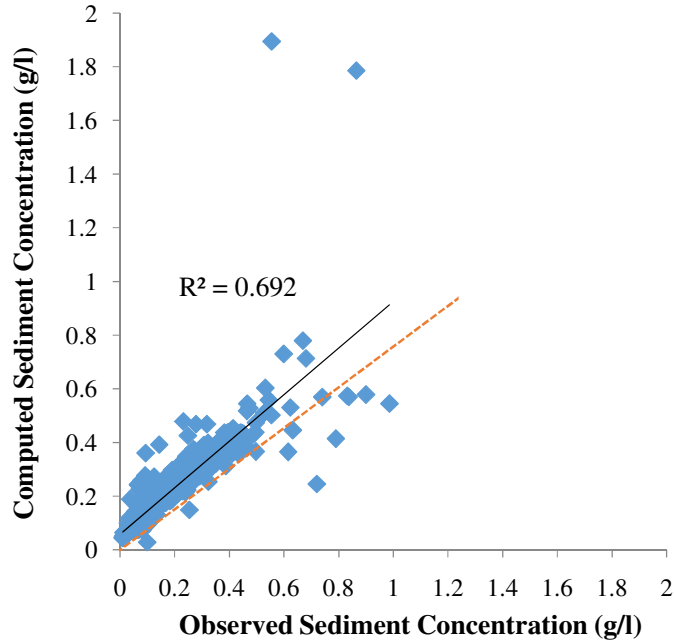


Fig. 4.12 Scatter plot of suspended sediment concentration using M-4 model during testing period at Champua station

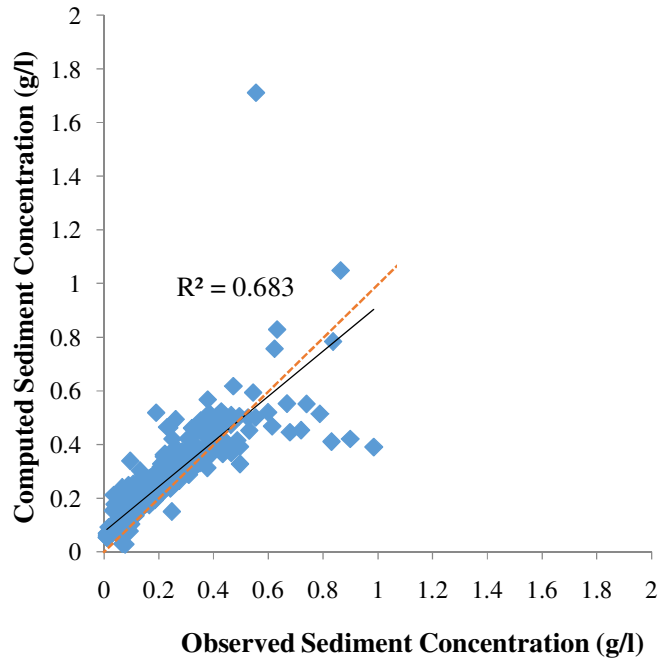


Fig. 4.13 Scatter plot of suspended sediment concentration using M-5 model during testing period at Champua station

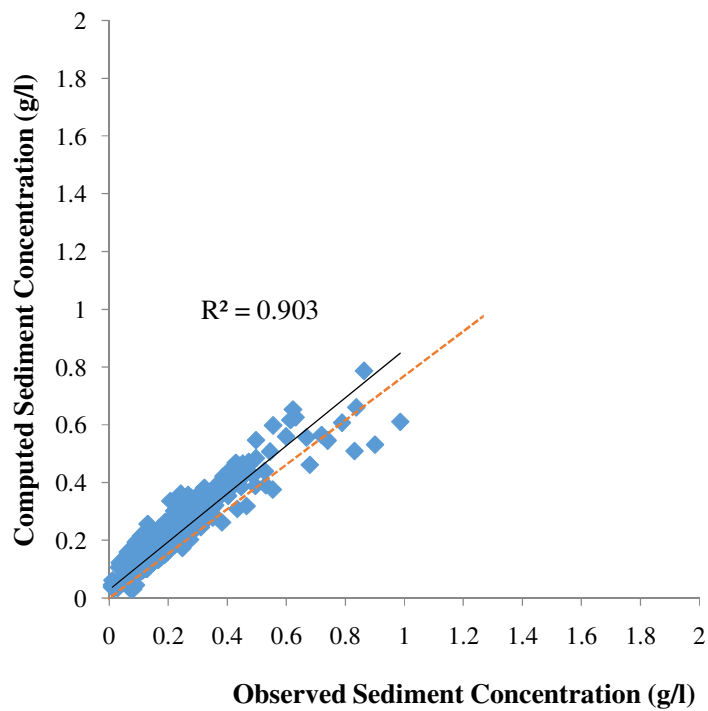


Fig. 4.14 Scatter plot of suspended sediment concentration using M-6 model during testing period at Champua station

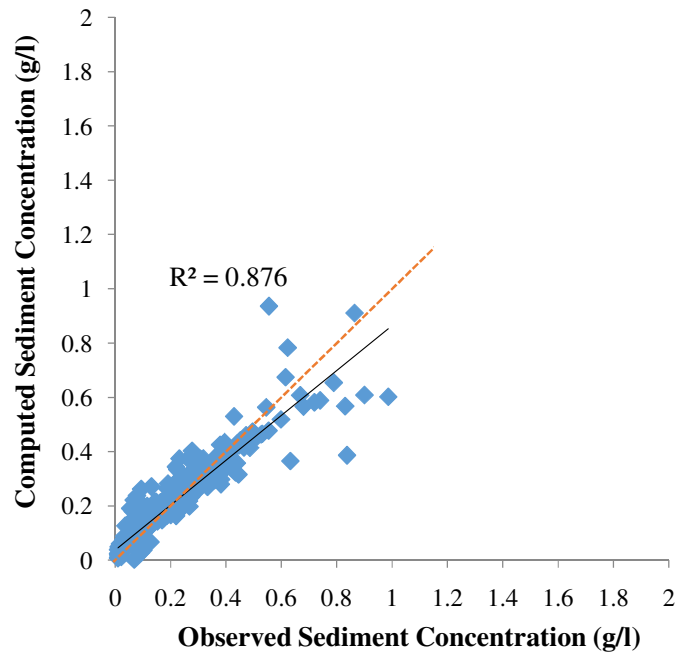


Fig. 4.15 Scatter plot of suspended sediment concentration using M-7 model during testing period at Champua station

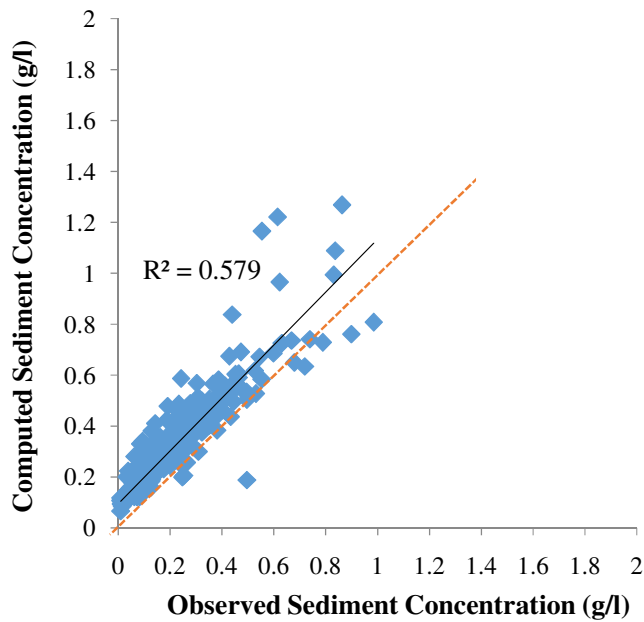


Fig. 4.16 Scatter plot of suspended sediment concentration using M-8 model during testing period at Champua station

4.1.1.2 Performance evaluation based on scatter plots

Scatter plots are plotted between computed suspended sediment concentration values on ordinate and their corresponding observed suspended sediment concentration values on the abscissa and are shown in Figs. 4.9 through 4.16 for models M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8 during testing period at Champua station. The observations of scatter diagrams on the basis of best fit line and 1:1 line indicate that the suspended sediment concentrations are over predicted for smaller values of suspended sediment concentration and under predicted for larger values of suspended sediment concentration using M-1, M-3, M-4, M-5, M-6 and M-7 models and over predicting for M-2 and M-8 models. It was also observed for M-3 model that most of the suspended sediment concentration values are under predicted and very few suspended sediment concentration values are over predicted.

The Figs. 4.14 and 4.15 for M-6 and M-7 models, respectively, nicely demonstrate that most of the data points are quite near the line of best fit in comparison to other models. But model M-7 shows some deviations from best fit line in comparison to M-6 model due to which performance of the M-7 model was found better than other models but inferior than M-6. Therefore, M-6 model was found to be better than other models for daily suspended sediment concentration prediction at Champua station. The values of coefficient of determination (R^2) for models M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8 are 0.588, 0.656, 0.727, 0.692, 0.683, 0.903, 0.876 and 0.579, respectively.

4.1.2 Quantitative performance evaluation of daily suspended sediment concentration models at Champua station

Quantitative evaluation is considered to be effective in performance evaluation of the models and free from personal bias which occurs in qualitative evaluation. Mean square error (MSE), normalized mean square error (NMSE), root mean square error (RMSE), coefficient of correlation (r), minimum description length (MDL), Akaike's information criterion (AIC) and coefficient of efficiency (CE) for suspended sediment concentration models at Champua station were calculated using Equation 3.14 to Equation 3.20 respectively. The values of indices for training and testing period at Champua station for all the models are given in Table 4.2 and Table 4.3, respectively.

It is clear from tables that the root mean square error (RMSE) for these five selected models varied from 0.0415 to 0.0439 g/l and 0.010 to 0.0205 g/l during training and testing periods, respectively. The values of correlation coefficient (r) varied from 0.835 to 0.848 and 0.850 to 0.951 during training and testing periods, respectively. The values of coefficient of efficiency (CE) during the training and testing periods ranged from 0.9809 to 0.9824 and 0.9736 to 0.9937, respectively. The models with coefficient of efficiency (CE) equal to or more than 0.9 were considered as very satisfactory, if coefficient of efficiency (CE) ranging from 0.8 to 0.9 then models were considered as fairly good and for less than 0.8 value of coefficient of efficiency (CE) models were considered as unsatisfactory (Shamseldin, 1997). Mean square error (MSE) values ranged from 0.00172 to 0.00187 g^2/l^2 and 0.00010 to 0.00042 g^2/l^2 during training and testing periods, respectively. The values of normalized mean square error (NMSE) during training and testing periods varied from 0.2832 to 0.3084 and 0.1013 to 0.4262, respectively. Also the values of Akaike's information criterion (AIC) during the training and testing period ranged between -15305.19 to -14953.67 and -11075.64 to -9082.56, respectively. The values of minimum description length (MDL) varied from -15130.27 to -14581.62 and -10949.82 to -8770.35 during the training and testing periods, respectively.

The models having minimum values of root mean square error (RMSE), normalized mean square error (NMSE), minimum description length (MDL), mean square error (MSE) and Akaike's information criterion (AIC) and higher values of coefficient of efficiency (CE) and coefficient of correlation (r) were considered as best models. Based on the selected criteria, five artificial neural networks based models i.e. M-3, M-4, M-5, M-6 and M-7 were found to be performing better than out of the eight models at Champua station.

Based on comparison among values of mean square error (MSE), Akaike's information criterion (AIC), coefficient of efficiency (CE), minimum description length (MDL), coefficient of correlation (r), normalized mean square error (NMSE) and root mean square error (RMSE) of five selected models at Champua station, M-6 model had the minimum values of mean square error (0.00010 g^2/l^2), normalized mean square error (0.1013), Akaike's information criterion (-11075.64), minimum description length (-10949.82) and root mean square error (0.0100 g/l) and maximum values of coefficient of efficiency (0.9937) and coefficient of correlation (0.951) in

Table 4.2 Performance evaluation indices of ANNs models for training period at Champua station of Baitarani river basin

Model	Network architecture	Training							
		No. of epochs ran	RMSE (g/l)	r	CE	MSE (g ² /l ²)	NMSE	AIC	MDL
M-1	2-10-10-1	296	0.0444	0.828	0.9799	0.00197	0.3244	-14870.23	-14564.38
M-2	3-10-10-1	245	0.0445	0.835	0.9798	0.00198	0.3260	-14838.67	-14513.82
M-3	4-10-10-1	127	0.0432	0.836	0.9809	0.00187	0.3084	-14953.67	-14609.83
M-4	5-6-6-1	196	0.0431	0.835	0.9810	0.00186	0.3060	-15152.90	-14980.03
M-5	6-10-10-1	51	0.0439	0.838	0.9812	0.00184	0.3022	-14963.46	-14581.62
M-6	7-5-5-1	84	0.0422	0.845	0.9818	0.00178	0.2923	-15284.14	-15130.27
M-7	8-6-6-1	74	0.0415	0.848	0.9824	0.00172	0.2832	-15305.19	-15098.13
M-8	9-10-10-1	71	0.0474	0.848	0.9770	0.00225	0.3708	-14404.32	-13965.50

Table 4.3 Performance evaluation indices of ANNs models for testing period Champua station of Baitarani river basin

Model	Network architecture	Testing							
		No. of epochs ran	RMSE (g/l)	r	CE	MSE (g^2/l^2)	NMSE	AIC	MDL
M-1	2-10-10-1	296	0.0251	0.780	0.9604	0.00063	0.6424	-8661.94	-8411.86
M-2	3-10-10-1	245	0.0224	0.831	0.9685	0.00050	0.5066	-8931.54	-8665.93
M-3	4-10-10-1	127	0.0176	0.853	0.9805	0.00031	0.3173	-9482.56	-9201.412
M-4	5-6-6-1	196	0.0192	0.852	0.9767	0.00037	0.3780	-9448.78	-9307.43
M-5	6-10-10-1	51	0.0205	0.850	0.9736	0.00042	0.4262	-9082.56	-8770.35
M-6	7-5-5-1	84	0.0100	0.951	0.9937	0.00010	0.1013	-11075.64	-10949.82
M-7	8-6-6-1	74	0.0114	0.937	0.9918	0.00013	0.1287	-10726.92	-10557.61
M-8	9-10-10-1	71	0.0283	0.775	0.9497	0.00080	0.8057	-8245.65	-7886.83

comparison to five selected models i.e. M-3, M-4, M-5 and M-7. The order of the models performance from best to worst at Champua station was found to be $M-6 > M-7 > M-3 > M-4 > M-5$. Therefore, performance of the M-6 model was found to be best in comparison to other models for prediction of daily suspended sediment concentration at Champua station.

On the basis of comparison between qualitative and quantitative evaluation for best model at Champua station, it was found that M-6 model in which present day suspended sediment concentration (SSC) depends on the present day discharge, one-two and three lag days discharge, one-two and three lag days suspended sediment concentration with (7-5-5-1) network architecture i.e. 7 input variables, five-five neurons in first and second hidden layer and single output processing element is best out of eight models.

4.1.3 Qualitative performance evaluation of daily suspended sediment concentration models at Anandpur station

Various artificial neural network architectures were applied using trial and error procedure and network architecture which were found to be best during testing and training periods at Anandpur station using qualitative evaluation are given in Table 4.4. The observed and the computed suspended sediment concentration for artificial neural networks based models were compared graphically using sediment hydrographs and scatter plots during testing period. The reason behind selection of testing periods of observed and the computed suspended sediment concentration was that, because during training period the model performance can be improved by over fitting the data and which can not be consider under selection of best models but model performance during testing period is independent of this.

4.1.3.1 Performance evaluation based on sediment hydrographs

Sediment hydrographs for qualitative evaluation are plotted between observed and computed suspended sediment concentration values on ordinate and their corresponding occurrence time on abscissa and are shown in Figs. 4.17 through 4.24 for models M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8, respectively during testing period at Anandpur station. It was observed from the sediment hydrographs that out of eight models, M-7 very closely predict the peaks accurately and rest of the models i.e. M-1, M-2, M-3, M-4, M-5, M-6 and M-8 over predict the peaks.

Table 4.4 Best selected network architecture for models at Anandpur station

Model	Network architecture	No. of epochs ran
M-1	2-7-7-1	23
M-2	3-9-9-1	22
M-3	4-4-4-1	26
M-4	5-10-10-1	32
M-5	6-8-8-1	35
M-6	7-6-1	22
M-7	8-4-4-1	22
M-8	9-5-5-1	35

4.1.3.2 Performance evaluation based on scatter plots

Scatter plots are plotted between computed suspended sediment concentration values on ordinate and corresponding observed suspended sediment concentration values on abscissa and are shown in Figs. 4.25 through 4.32 for models M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8, respectively during testing period at Anandpur station. The observations of scatter diagrams on the basis of best fit line and 1:1 line indicate that the suspended sediment concentrations are over predicted for smaller values of suspended sediment concentration and under predicted for larger values of suspended sediment concentration using M-1, M-4, M-5, M-6 and M-7 models and over predicting for M-2 and M-8 models. It was also observed for model M-7 that most of the suspended sediment concentration values are under predicted and very few suspended sediment concentration values are over predicted. The values of coefficient of determination (R^2) for M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8 models are 0.986, 0.659, 0.670, 0.667, 0.673, 0.674, 0.703 and 0.571, respectively.

It is observed from the scatter plot of model M-1 that all the data points are very closely near to the line of best fit. Therefore, the M-1 model is found best in comparison to eight models for prediction of daily suspended sediment concentration at Anandpur station.

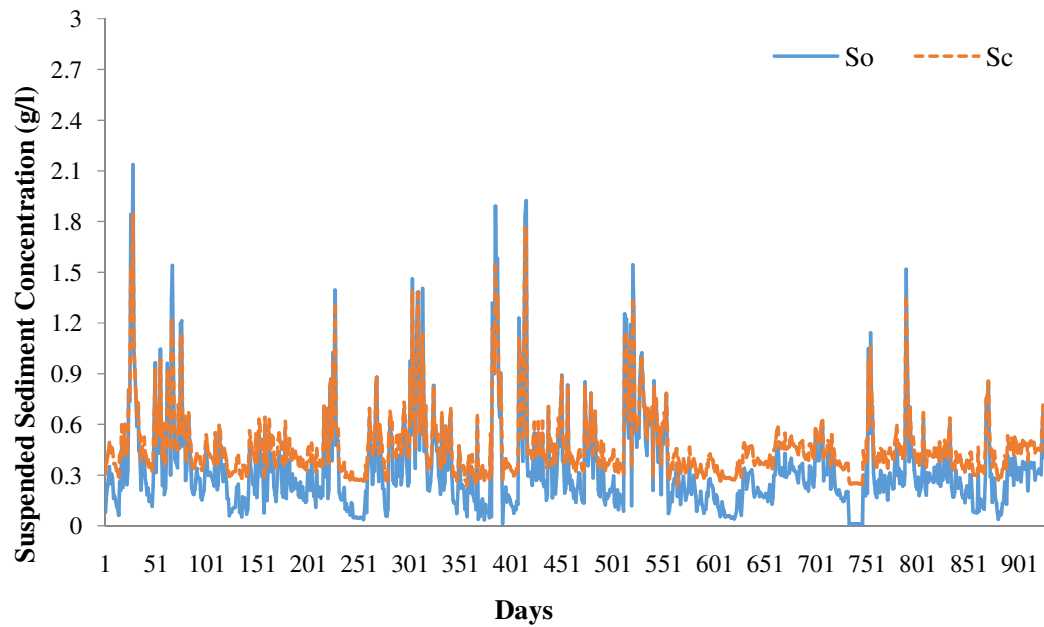


Fig. 4.17 Observed (So) and computed (Sc) suspended sediment concentration using M-1 model during testing period at Anandpur station

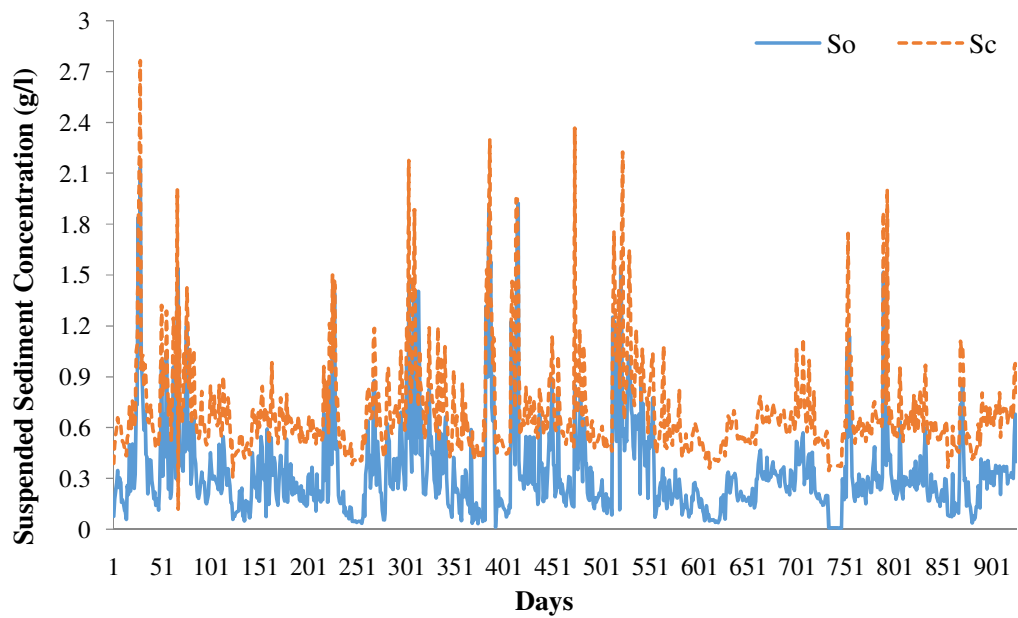


Fig. 4.18 Observed (So) and computed (Sc) suspended sediment concentration using M-2 model during testing period at Anandpur station

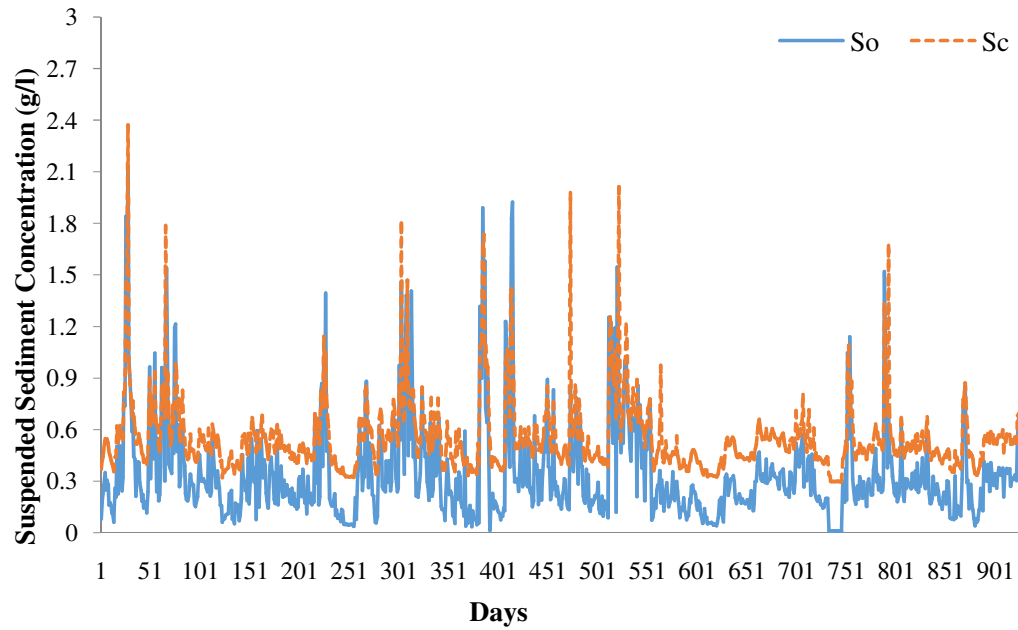


Fig. 4.19 Observed (So) and computed (Sc) suspended sediment concentration using M-3 model during testing period at Anandpur station

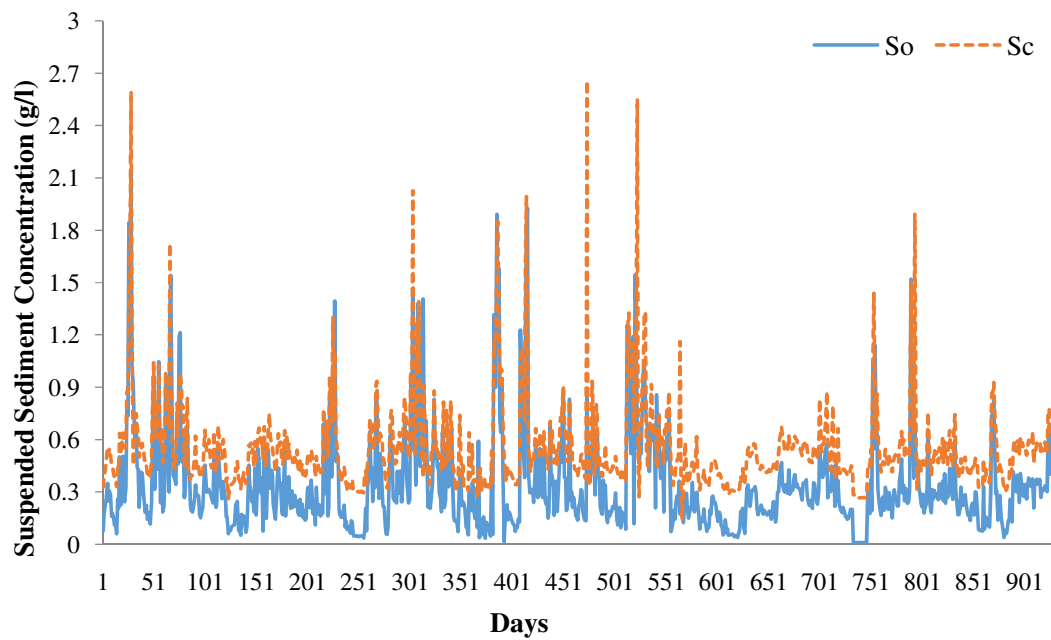


Fig. 4.20 Observed (So) and computed (Sc) suspended sediment concentration using M-4 model during testing period at Anandpur station

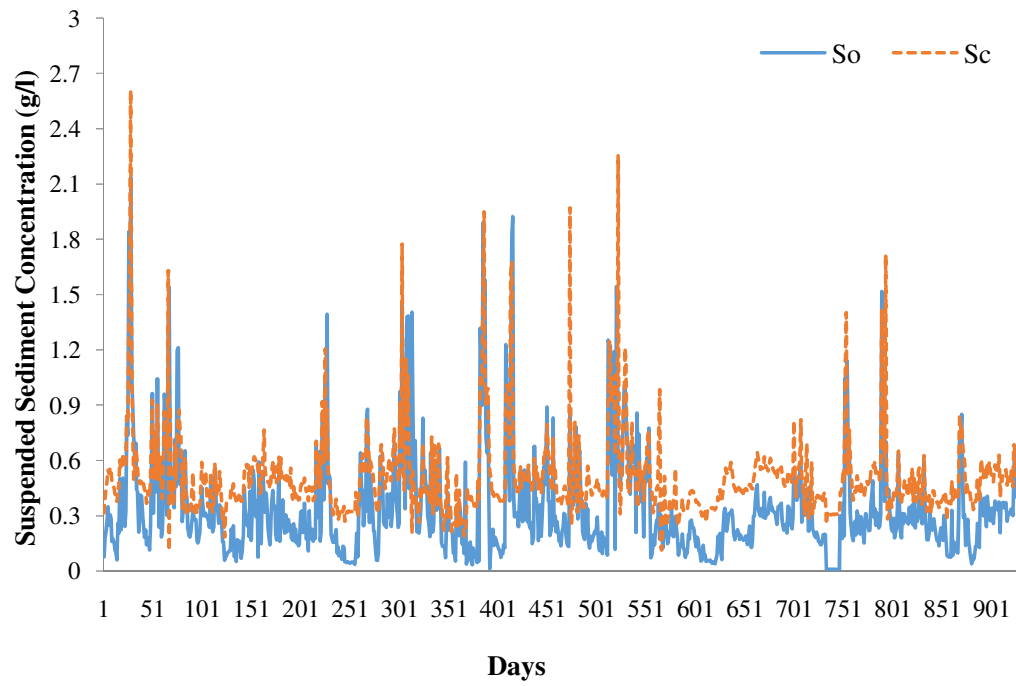


Fig. 4.21 Observed (S_o) and computed (S_c) suspended sediment concentration using M-5 model during testing period at Anandpur station

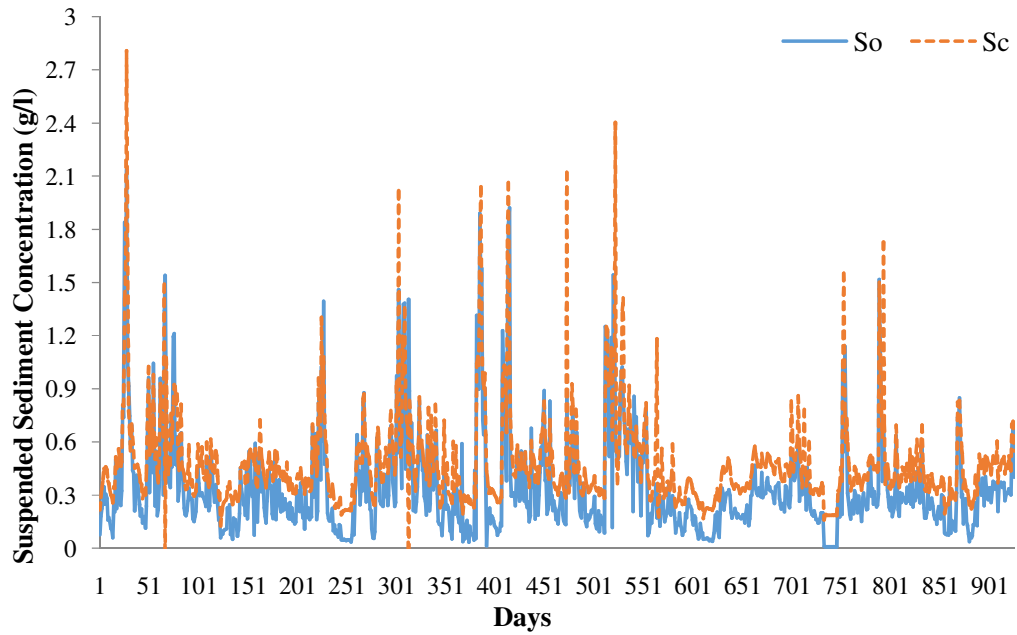


Fig. 4.22 Observed (S_o) and computed (S_c) suspended sediment concentration using M-6 model during testing period at Anandpur station

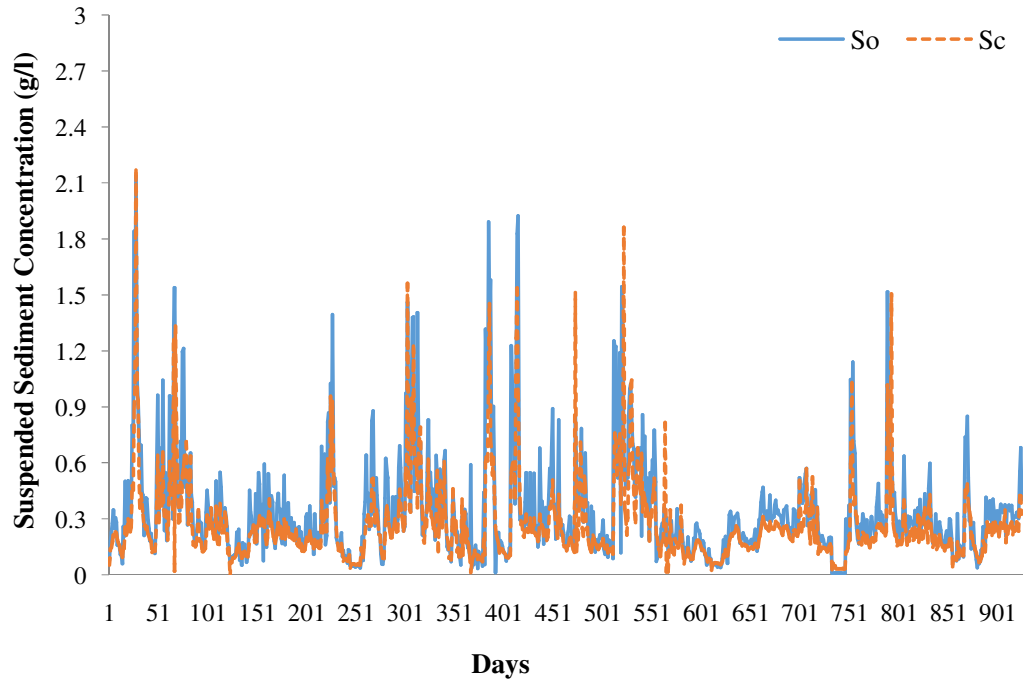


Fig. 4.23 Observed (S_o) and computed (S_c) suspended sediment concentration using M-7 model during testing period at Anandpur station

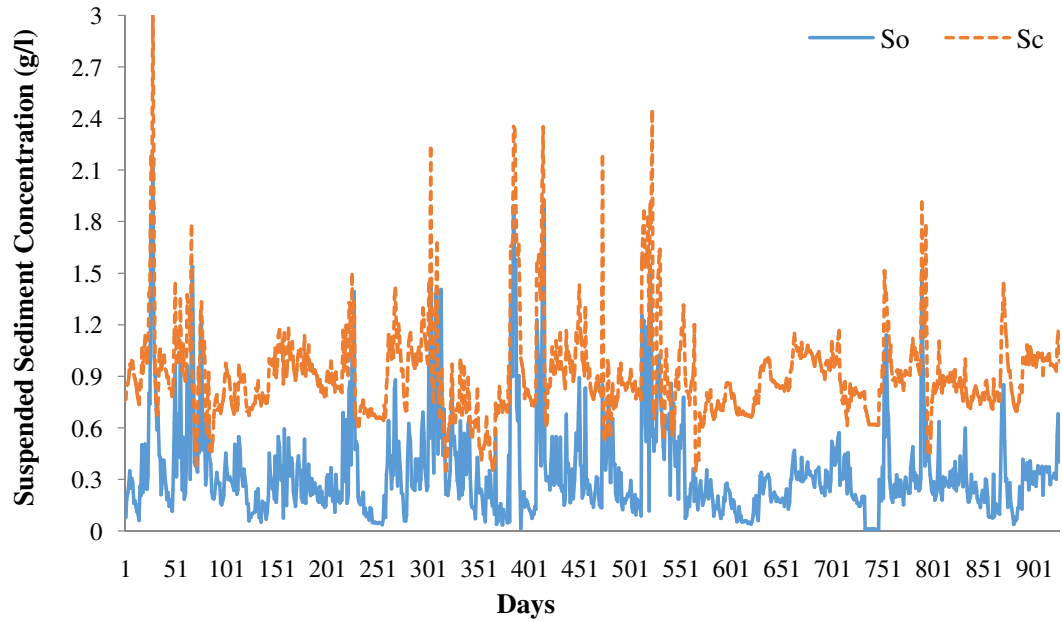


Fig. 4.24 Observed (S_o) and computed (S_c) suspended sediment concentration using M-8 model during testing period at Anandpur station

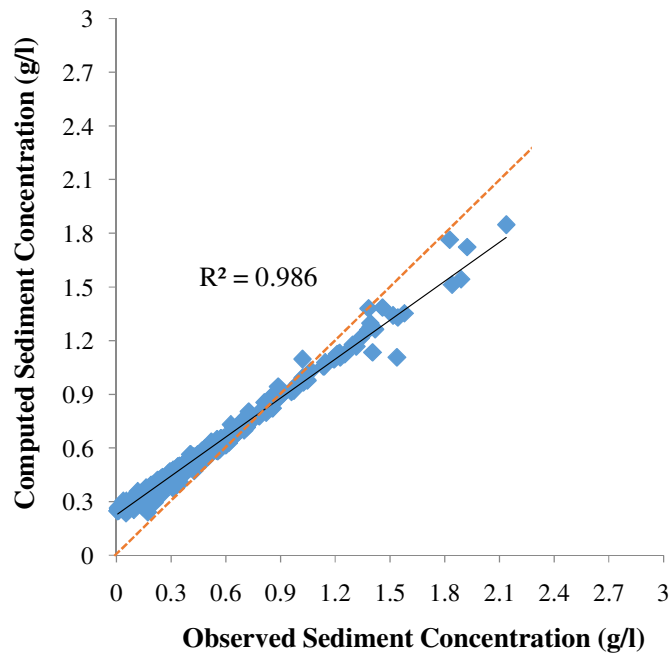


Fig. 4.25 Scatter plot of suspended sediment concentration using M-1 model during testing period at Anandpur station

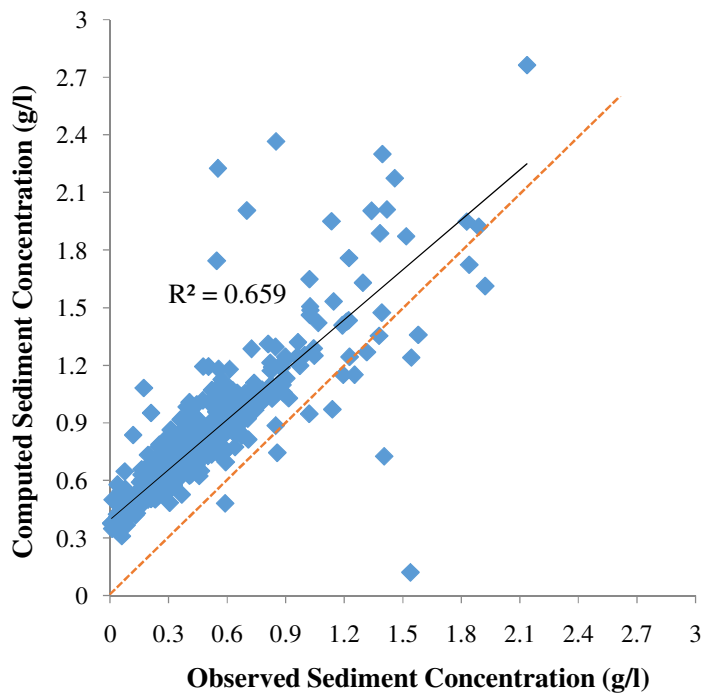


Fig. 4.26 Scatter plot of suspended sediment concentration using M-2 model during testing period at Anandpur station

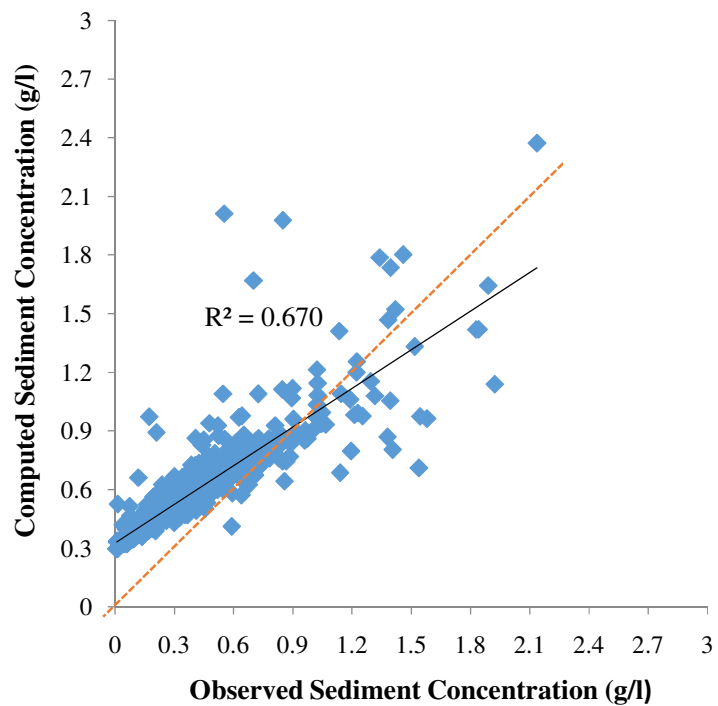


Fig. 4.27 Scatter plot of suspended sediment concentration using M-3 model during testing period at Anandpur station

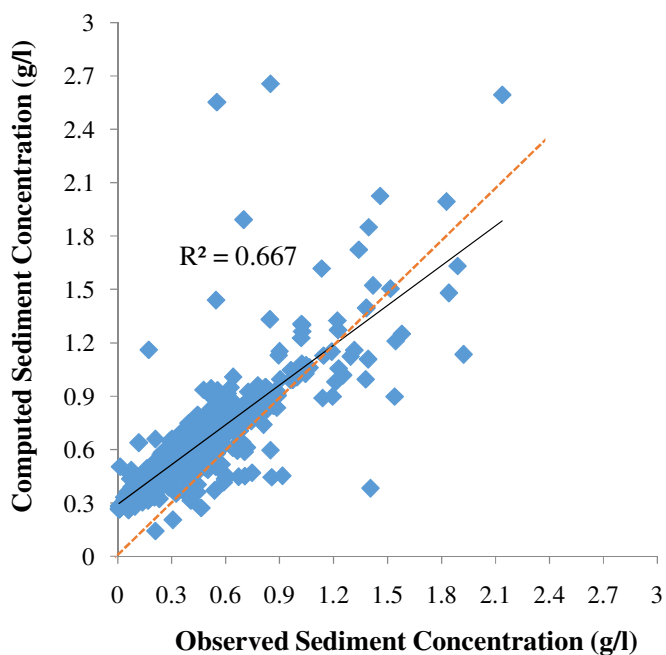


Fig. 4.28 Scatter plot of suspended sediment concentration using M-4 model during testing period at Anandpur station

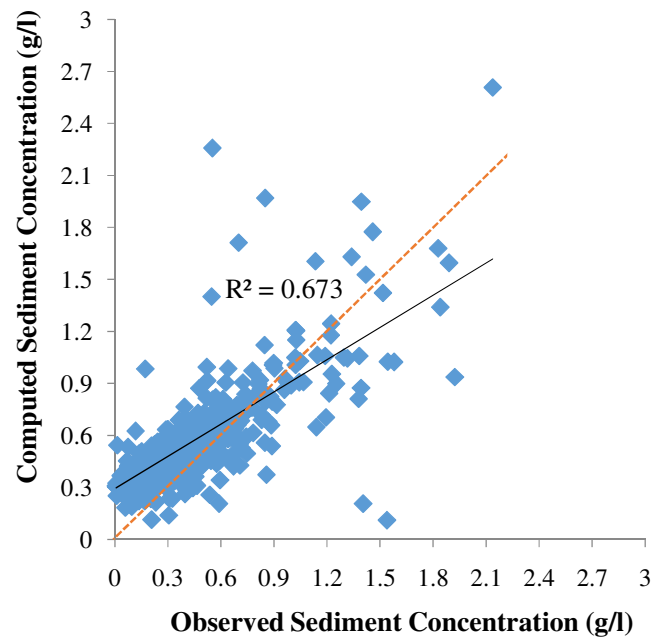


Fig. 4.29 Scatter plot of suspended sediment concentration using M-5 model during testing period at Anandpur station

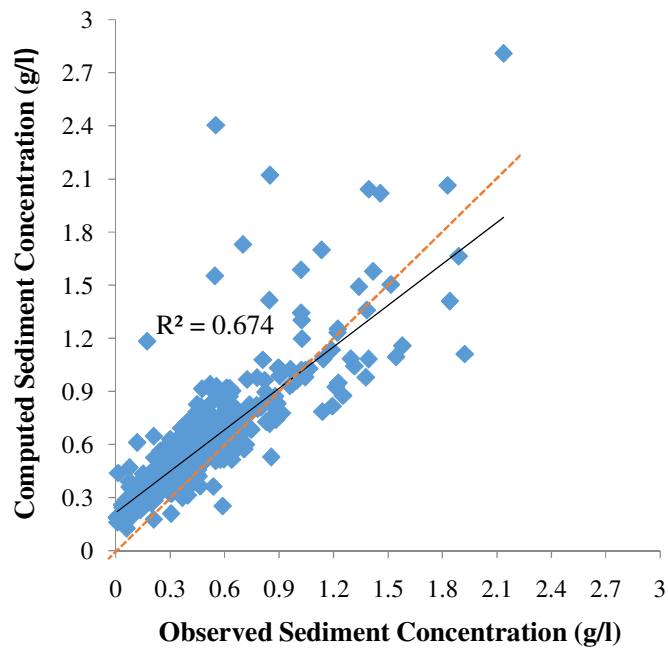


Fig. 4.30 Scatter plot of suspended sediment concentration using M-6 model during testing period at Anandpur station

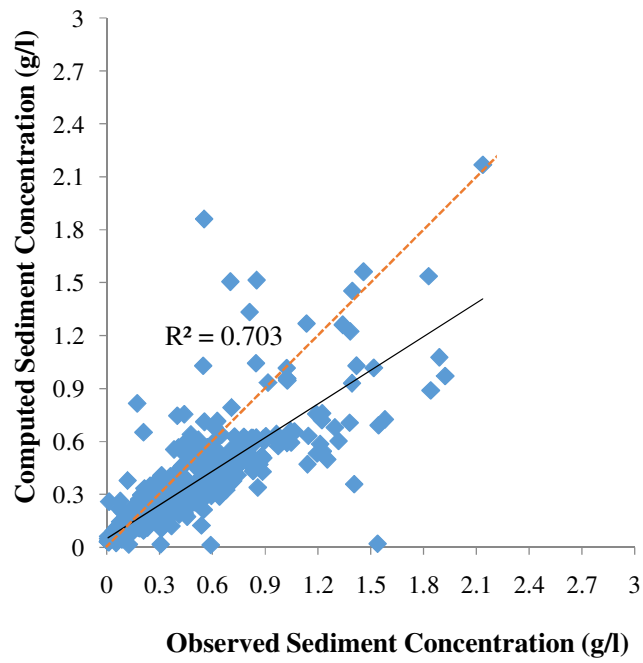


Fig. 4.31 Scatter plot of suspended sediment concentration using M-7 model during testing period at Anandpur station

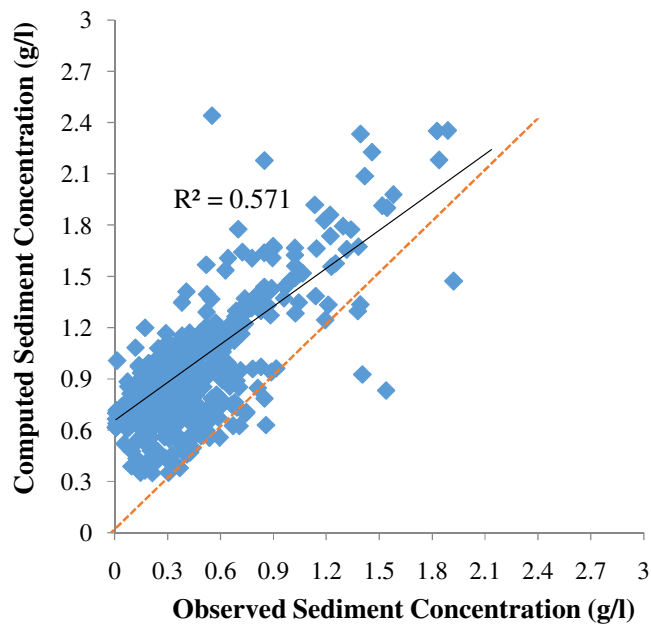


Fig. 4.32 Scatter plot of suspended sediment concentration using M-8 model during testing period at Anandpur station

4.1.4 Quantitative evaluation of suspended sediment concentration models at Anandpur station

Mean square error (MSE), normalized mean square error (NMSE), root mean square error (RMSE), coefficient of correlation (r), minimum description length (MDL), Akaike's information criterion (AIC) and coefficient of efficiency (CE) for suspended sediment concentration models at Anandpur station were calculated using Equation 3.14 to Equation 3.20, respectively. Performance evaluation indices for models during training and testing period at Anandpur station are given in Table 4.5 and 4.6, respectively.

It is clear from Tables that the root mean square error (RMSE) for these five selected models varied from 0.0295 to 0.0305 g/l and 0.0071 to 0.0114 g/l during training and testing periods, respectively. The values of correlation coefficient (r) varied from 0.473 to 0.537 and 0.833 to 0.993 during training and testing periods, respectively. The values of coefficient of efficiency (CE) during the training and testing periods ranged from 0.9984 to 0.9985 and 0.9984 to 0.9994, respectively. Mean square error (MSE) values ranged from 0.00087 to 0.00093 g^2/l^2 and 0.00005 to 0.00013 g^2/l^2 during training and testing periods, respectively. The values of normalized mean square error (NMSE) during training and testing periods varied from 0.7395 to 0.7920 and 0.3050 to 0.8078, respectively. Also the values of Akaike's information criterion (AIC) during the training and testing period ranged between -17086.21 to -16882.53 and -11895.47 to -10754.75, respectively. The values of minimum description length (MDL) varied from -16993.13 to -16621.21 and -11752.57 to -10529.52 during the training and testing periods, respectively.

Based on the selected criteria, five artificial neural networks based models i.e. M-1, M-3, M-5, M-6 and M-7 were found to be performing better than out of the eight models. On the basis of comparison among values of mean square error (MSE), normalized mean square error (NMSE), Akaike's information criterion (AIC), coefficient of efficiency (CE), minimum description length (MDL), coefficient of correlation (r) and root mean square error (RMSE) of five selected artificial neural networks based models, it was found that M-1 model is the best performing model at Anandpur station. M-1 model had the minimum values of mean square error (0.00005 g^2/l^2), Akaike's information criterion (-11895.47), minimum description length (-11752.57), normalized mean square error (0.3050), and root mean square error

Table 4.5 Performance evaluation indices of ANNs models for training periods at Anandpur station of Baitarani river basin

Model	Network architecture	Training							
		No. of epochs ran	RMSE (g/l)	r	CE	MSE (g ² /l ²)	NMSE	AIC	MDL
M-1	2-7-7-1	23	0.0302	0.473	0.9984	0.00091	0.7810	-16882.53	-16707.76
M-2	3-9-9-1	22	0.0329	0.511	0.9981	0.00108	0.9179	-16382.43	-16106.98
M-3	4-4-4-1	26	0.0295	0.537	0.9985	0.00087	0.7442	-17086.21	-16993.13
M-4	5-10-10-1	32	0.0297	0.535	0.9984	0.00088	0.7476	-16791.23	-16428.39
M-5	6-8-8-1	35	0.0295	0.519	0.9985	0.00087	0.7435	-16896.66	-16621.21
M-6	7-6-1	22	0.0295	0.523	0.9985	0.00087	0.7395	-17077.56	-16961.68
M-7	8-4-4-1	22	0.0305	0.515	0.9984	0.00093	0.7920	-16902.27	-16778.79
M-8	9-5-5-1	35	0.0377	0.569	0.9975	0.00142	1.2128	-15811.11	-15638.24

Table 4.6 Performance evaluation indices of ANNs models for testing periods at Anandpur station of Baitarani river basin

Model	Network architecture	Testing							
		No. of epochs ran	RMSE (g/l)	r	CE	MSE (g ² /l ²)	NMSE	AIC	MDL
M-1	2-7-7-1	23	0.0071	0.993	0.9994	0.00005	0.3050	-11895.47	-11752.57
M 2	3-9-9-1	22	0.0173	0.828	0.9962	0.00030	1.7983	-9624.84	-9399.61
M-3	4-4-4-1	26	0.0114	0.833	0.9984	0.00013	0.8078	-10793.12	-10717.01
M 4	5-10-10-1	32	0.0118	0.831	0.9982	0.00014	0.8275	-10479.72	-10183.04
M-5	6-8-8-1	35	0.0110	0.835	0.9985	0.00012	0.7122	-10754.75	-10529.52
M-6	7-6-1	22	0.0095	0.838	0.9989	0.00009	0.5599	-11216.42	-11121.67
M-7	8-4-4-1	22	0.0078	0.839	0.9992	0.00006	0.3699	-11714.22	-11613.25
M-8	9-5-5-1	35	0.0268	0.753	0.9909	0.00072	4.3884	-8644.41	-8503.06

(0.0071 g/l) and maximum values of coefficient of efficiency (0.9994) and coefficient of correlation (0.993) in comparison to M-3, M-5, M-6 and M-7 models during testing period at Anandpur station. Therefore, the performance of the M-1 model was found to be best for prediction of daily suspended sediment concentration at Anandpur station. The order of models performance from best to worst for five selected models at Anandpur station was found to be $M-1 > M-7 > M-6 > M-5 > M-3$.

On the basis of comparison between qualitative and quantitative evaluation for best model at Anandpur station, the M-1 model in which present day suspended sediment concentration (SSC) depends on the present day discharge and one lag day suspended sediment concentration with (2-7-7-1) network architecture i.e. 2 input variables, seven-seven neurons in first and second hidden layers and single output processing element is found to be best out of eight models.

Based on different qualitative and quantitative evaluation criterion during testing periods for all models taken together, it was observed that the M-6 model with (7-5-5-1) network architecture i.e. 7 input variables (i.e. present day discharge, one-two and three lag days discharge, one-two and three lag days suspended sediment concentration), five neurons in first hidden layer, five neurons in second hidden layer and single output processing element was found to be best out of all models at Champua station. At Anandpur station the M-1 model with (2-7-7-1) network architecture i.e. 2 input variables (i.e. present day discharge and one lag day suspended sediment concentration), seven neurons in first hidden layer, seven neurons in second hidden layer and single output processing element was found to be best out of all models. The selection of different best models i.e. M-6 at Champua station located at the top and M-1 at Anandpur station located at the outlet of the Baitarani river basin indicated that there are much geologic, hydrologic and geometric dissimilarity at both the stations.

Quantitative and qualitative performance evaluation during testing periods at both the stations of Baitarani river basin indicated that artificial neural networks based models can be successfully applied for the prediction of daily suspended sediment concentration using present and previous day/days discharges and previous day/days suspended sediment concentrations.

*Summary
and
Conclusions*

5. SUMMARY AND CONCLUSIONS

Artificial neural networks based models were developed to predict daily suspended sediment concentration for the Baitarani river at Anandpur and Champua stations using daily discharge and daily suspended sediment concentration. The 30 years data (June 1977 to September 2006) used in this study was divided into two sets viz. a training set (1977-1996) for model calibration and a testing set (1997-2006) for validation of models developed for both the stations.

Artificial neural networks based daily suspended sediment concentration models were developed by using present day discharge (Q_t) along with the different combinations of previous days discharges ($Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$ and $Q_{(t-4)}$) and previous days suspended sediment concentrations ($S_{(t-1)}$, $S_{(t-2)}$, $S_{(t-3)}$ and $S_{(t-4)}$) for the prediction of present day suspended sediment concentration (S_t). Eight models for Anandpur and Champua stations were developed by using various combinations of discharge and suspended sediment concentration.

ANNs models were calibrated by using multilayer feedforward back propagation neural networks for maximum epochs of 1000 and threshold value of 0.001 with varying number of neurons i.e. from 1 to 10 in single and double hidden layer using sigmoid activation function and Levenberg-Marquardt (L-M) learning algorithm for both the stations of Baitarani river basin.

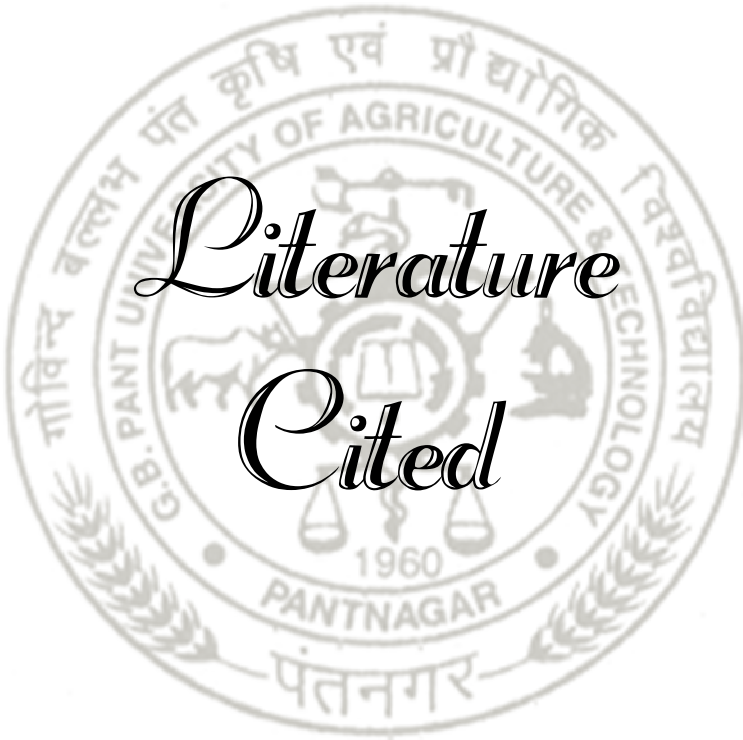
The performance of the developed models was evaluated qualitatively by visual observations and quantitatively. In qualitative evaluation of models, the observed and the computed suspended sediment concentration for artificial neural networks based models were compared graphically using sediment hydrographs and scatter plots during testing period at Champua station and Anandpur station. Akaike's information criterion (AIC), correlation coefficient (r), mean square error (MSE), root mean square error (RMSE), minimum description length (MDL), coefficient of efficiency (CE) and normalized mean square error (NMSE) indices were used for quantitative performance evaluation of the models.

There are following conclusions are drawn from the results of the study;

1. It was observed from sediment hydrographs at Champua station, that out of eight models M-3, M-6 and M-7 very closely predict the peaks accurately and rest of the models i.e. M-1, M-2, M-4, M-5 and M-8 over predict the peaks. The observations of scatter diagrams on the basis of best fit line and 1:1 line indicated that the suspended sediment concentrations are over predicted for smaller values of SSC and under predicted for larger values of SSC using M-1, M-3, M-4, M-5, M-6 and M-7 models and over predicting for M-2 and M-8 models. The M-6 model shows that most of the data points in scatter plot are quite near the line of best fit in comparison to other models. Therefore, on the basis of qualitative evaluation, M-6 model was found to be better than other models for daily suspended sediment concentration prediction at Champua station.
2. M-6 model had the minimum values of mean square error (MSE), normalized mean square error (NMSE), Akaike's information criterion (AIC), minimum description length (MDL) and root mean square error (RMSE) in comparison to five selected models i.e. M-3, M-4, M-5 and M-7 and the values are $0.00010 \text{ g}^2/\text{l}^2$, 0.1013, -11075.64, -10949.82, 0.0100 g/l, respectively. Whereas 0.9937 and 0.951 are the values of coefficient of efficiency (CE) and coefficient of correlation (r) respectively and these values were found to be maximum in comparison to five selected models i.e. M-3, M-4, M-5 and M-7 during testing period at Champua station.
3. On the basis of qualitative and quantitative evaluation at Champua station, it is observed that the M-6 model whose performance suggested that present day suspended sediment concentration (SSC) depends on the present day discharge, one-two and three lag days discharge, one-two and three lag days suspended sediment concentration with (7-5-5-1) network architecture i.e. 7 input variables, five-five neurons in first and second hidden layer and single output processing element is found to be best out of all models.
4. It was observed from sediment hydrographs at Anandpur station, that out of eight models, M-7 very closely predict the peaks accurately and rest of the models i.e. M-1, M-2, M-3, M-4, M-5, M-6 and M-8 over predict the peaks.

The observations of scatter diagrams on the basis of best fit line and 1:1 line indicated that the SSC are over predicted for smaller values of SSC and under predicted for larger values of SSC using M-1, M-3, M-4, M-5, M-6 and M-7 models and over predicting for M-2 and M-8 models. It was also observed in the scatter plots of models that for M-1 model all the data points are very closely near to the line of best fit out of scatter plots of eight models. Therefore, M-1 model was found best in comparison to eight models for prediction of daily suspended sediment concentration at Anandpur station.

5. It was observed that M-1 model had the minimum values of mean square error (MSE), normalized mean square error (NMSE), Akaike's information criterion (AIC), minimum description length (MDL) and root mean square error (RMSE) in comparison to five selected models i.e. M-3, M-5, M-6 and M-7 and these values are $0.00005 \text{ g}^2/\text{l}^2$, 0.3050, -11895.47, -11752.57, 0.0071 g/l, respectively. The values of coefficient of efficiency (CE) and coefficient of correlation (r) are 0.9994 and 0.993 respectively for M-1 model and these values were found to be maximum in comparison to five selected models i.e. M-3, M-5, M-6 and M-7 during testing period at Anandpur station
6. It was observed that the M-1 model whose performance suggested that present day suspended sediment concentration (SSC) depends on the present day discharge and one lag day suspended sediment concentration with (2-7-7-1) network architecture i.e. 2 input variables, seven neurons in first hidden layer, seven neurons in second hidden layer and single output processing element is found to be best out of eight models based on qualitative and quantitative evaluation at Anandpur station.
7. Artificial neural networks based suspended sediment concentration models can be successfully applied for the prediction of daily suspended sediment concentration at Champua and Anandpur stations of Baitarani river.



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VITAE

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ABSTRACT

Eight artificial neural networks based models were developed to predict daily suspended sediment concentration for the Baitarani river at Anandpur and Champua stations using daily discharge and daily suspended sediment concentration. The 30 years data (June 1977 to September 2006) used in this study was divided into two sets viz. a training set (1977-1996) and a testing set (1997-2006). ANNs models were calibrated by using multilayer feedforward back propagation neural networks with sigmoid activation function and Levenberg-Marquardt (L-M) learning algorithm. The performance of the developed models was evaluated qualitatively and quantitatively. In qualitative evaluation of models, the observed and the computed suspended sediment concentration were compared using sediment hydrographs and scatter plots during testing period. Akaike's information criterion (AIC), correlation coefficient (r), mean square error (MSE), root mean square error (RMSE), minimum description length (MDL), coefficient of efficiency (CE) and normalized mean square error (NMSE) indices were used for quantitative performance evaluation of the models. Results on the basis of qualitative and quantitative evaluation indicate that M-6 model with (7-5-5-1) network architecture is better than all models at Champua station and M-1 model with (2-7-7-1) network architecture is better than all models at Anandpur station.


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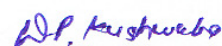

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विभाग	: मृदा एवं जल संरक्षण अभियांत्रिकी		
शोध ग्रन्थ शीर्षक	: "कृत्रिम तंत्रिका नेटवर्क का उपयोग करते हुए निलंबित तलछट उपज मॉडलिंग"		
परामर्शदाता	: डॉ० देवेन्द्र कुमार		

सारांश

दैनिक निलंबित तलछट एकाग्रता की भविष्यवाणी करने के लिए दैनिक प्रवाह एवं दैनिक निलंबित तलछट एकाग्रता का उपयोग कर वैतरणी नदी के आनंदपुर एवं चम्पुआ स्टेशनों पर आठ कृत्रिम तंत्रिका नेटवर्क पर आधारित मॉडल विकसित किये गये। इस अध्ययन में उपयोग किये गये 30 वर्षों के आँकड़ों को दो सेटों यानी एक प्रशिक्षण सेट (1977-1996) एवं एक परिक्षण सेट (1997-2006) में विभाजित किया गया। बहुपरत आगे फीड वापस प्रसार तंत्रिका नेटवर्क के साथ अवग्रह संक्रियण फलन एवं लेबनवर्ग-मारक्वार्ट (एल०एम०) सीखने एल्गोरिथ्म का उपयोग कर ए०एन०एन० मॉडलों को जाँचा गया। विकसित मॉडलों के प्रदर्शन का मुल्यांकन गुणात्मक एवं मात्रात्मक रूप से किया गया। मॉडलों के गुणात्मक मुल्यांकन में, परिक्षण अवधि के दौरान तलछट हाइड्रो रेखांकन एवं बिखराव भूखंडों का उपयोग कर अनुसरणीय एवं गणनिय निलंबित तलछट एकाग्रता की तुलना की गयी। मॉडलों के मात्रात्मक प्रदर्शन मुल्यांकन के लिए अकाईके की जानकारी कसौटी (ए०आई०सी०), सहसंबंध गुणांक (आर), औसत वर्ग त्रुटि (एम०एस०ई०), मुल औसत वर्ग त्रुटि (आर०एम०एस०ई०), न्यूनतम विवरण लंबाई (एम०डी०एल०), दक्षता के गुणांक (सी०ई०) एवं सामान्यीकृत औसत वर्ग त्रुटि (एन०एम०एस०ई०) सुचकांकों का इस्तेमाल किया गया। गुणात्मक एवं मात्रात्मक मुल्यांकनों के आधार पर चम्पुआ स्टेशन पर एम-6 मॉडल (7-5-5-1) नेटवर्क वास्तुकला के साथ सभी मॉडलों की तुलना में बेहतर है और आनंदपुर स्टेशन पर एम-1 मॉडल (2-7-7-1) नेटवर्क वास्तुकला साथ सभी मॉडलों की तुलना में बेहतर पाये गये।


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